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# Cognitive and Neural Processes of Constucted Preferences

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# Cognitive and Neural Processes of Constucted Preferences

## Abstract

Past research has identified many ways in which decisions are influenced by the context of the decision environment. In this dissertation, we use eye-tracking and functional magnetic resonance imaging (fMRI) to investigate the processes and strategies individuals use in different decision contexts. The first two chapters use eye-tracking to extract fine-grained process data that uncover the different strategies that individuals employ in response to changes in the decision environment. Chapter 2 investigates how decision processes change in response to different modes of preference elicitation. We find that preferences for gambles shift between choice and bid elicitation. More importantly, these preference reversals are accompanied by differential attention to gamble attributes (probability of winning versus amount to win), suggesting that these reversals are due to differential weighting of these attributes in the two contexts. Chapter 3 uses eye-tracking to investigate how decision strategies shift as the number of options and time pressure increases. In response to an increasing number of choice options, all subjects consider only a subset of the options before making a decision, in which the value of a single attribute (the probability of winning) has the largest effect on whether an option is considered. Critically, those experiencing time pressure tended to then use a simpler attribute-based strategy to choose amongst the subset of options considered, while those not under time pressure tended to use a compensatory tradeoff-based strategy. Chapter 3 highlights how eye-tracking can be especially useful in detecting subtle changes in decision strategies. In the final study, we use fMRI data and multi-voxel pattern analysis to understand how decision strategies are represented in the brain. Overall, we find that different forms of task complexity recruit similar neural regions across the frontal and parietal cortices, which have previously been implicated as responding in a non-specific manner to general cognitive demands. However, inconsistent with a general or non-specific role in cognitive demand, multi-voxel pattern analysis can distinguish different forms of task complexity in all of these regions. Given that different forms of task complexity evoke different decision strategies, this suggests that fMRI could potentially be used to decode or predict the decision strategies individuals are using. Taken together, this work furthers our understanding of how decision processes changes in response to changes in the task context and suggests important future directions for using eye-tracking and fMRI to identify the processes and strategies individuals use to make a decision.

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COGNITIVE AND NEURAL PROCESSES OF CONSTRUCTED PREFERENCES

Betty Kim Viechnicki

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Psychology

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

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COGNITIVE AND NEURAL PROCESSES OF CONSTRUCTIVE PREFERENCES

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## ABSTRACT

### COGNITIVE AND NEURAL PROCESSES OF CONSTRUCTED PREFERENCES

Betty K. Viechnicki

Joseph W. Kable

Past research has identified many ways in which decisions are influenced by the context of the decision environment. In this dissertation, we use eye-tracking and functional magnetic resonance imaging (fMRI) to investigate the processes and strategies individuals use in different decision contexts. The first two chapters use eye-tracking to extract fine-grained process data that uncover the different strategies that individuals employ in response to changes in the decision environment. Chapter 2 investigates how decision processes change in response to different modes of preference elicitation. We find that preferences for gambles shift between choice and bid elicitations. More importantly, these preference reversals are accompanied by differential attention to gamble attributes (probability of winning versus amount to win), suggesting that these reversals are due to differential weighting of these attributes in the two contexts. Chapter 3 uses eye-tracking to investigate how decision strategies shift as the number of options and time pressure increases. In response to an increasing number of choice options, all subjects consider only a subset of the options before making a decision, the value of a single attribute (the probability of winning) having the largest effect on whether an option is considered. Critically, those experiencing time pressure tended to then use a simpler attribute-based strategy to choose amongst the subset of options considered, while those not under time pressure tended to use a compensatory tradeoff-based strategy. Chapter 3 highlights how eye-tracking can be especially

useful in detecting subtle changes in decision strategies. In the final study, we use fMRI data and multi-voxel pattern analysis to understand how decision strategies are represented in the brain. Overall, we find that different forms of task complexity recruit similar neural regions across the frontal and parietal cortices, which have previously been implicated as responding in a non-specific manner to general cognitive demands. However, inconsistent with a general or non-specific role in cognitive demand, multi-voxel pattern analysis can distinguish different forms of task complexity in all of these regions. Given that different forms of task complexity evoke different decision strategies, this suggests that fMRI could potentially be used to decode or predict the decision strategies individuals are using. Taken together, this work furthers our understanding of how decision processes changes in response to changes in the task context and suggests important future directions for using eye-tracking and fMRI to identify the processes and strategies individuals use to make a decision.

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## CHAPTER 1 – Introduction

The way people make decisions has long been a subject of intense study by educators, business people, and researchers. A long-standing approach to understanding how people make decisions is assuming a rational choice framework, where the decision maker has well-defined, stable preferences that do not depend on the circumstances of the decision environment. Therefore, the decision maker's choice among different options should be consistent, coherent, and determined only by relevant results (McFadden, 1999). For example, if an individual is willing to wait longer to eat at restaurant A than to eat at restaurant B, then the individual should also be willing to pay more to eat at restaurant A than at restaurant B (consistency). If an individual is willing to pay more to eat at restaurant A than at restaurant B, and more for restaurant B than restaurant C, then the individual should be willing to pay more for restaurant A than restaurant C (coherence). If a new restaurant opened, restaurant D, then the choice between eating at restaurant B and restaurant C should not depend on whether the irrelevant restaurant D option is included in the choice set.

Yet, decades of psychological research have demonstrated that people often do not behave in line with rationality, and individuals may not always exhibit consistent and well-defined preferences (for reviews, see Kahneman, Slovic, and Tversky, 1982; Mellers, Schwartz, and Cooke, 1998; Shafir and LeBoeuf, 2002). For instance, individuals may change their preference for one option over another when a third option is introduced (Huber, Payne, and Puto, 1982), and preferences for insurance coverage may change depending on how premiums are framed (Johnson et al., 1993). Additionally, a classic example, coined the preference reversal phenomenon, demonstrated that individuals prefer gamble A over gamble

B when making a choice between the two, but when making a numerical evaluation of the two gambles, individuals prefer gamble B over gamble A (Lichtenstein and Slovic, 1971). This finding has been replicated many times in spite of efforts to try to eradicate the effect (Grether and Plott, 1979).

Alternative frameworks to rational choice theory have been suggested for how people make decisions. One viewpoint is that individuals do not necessarily construct preferences, but instead make decisions based on rules and heuristics (March, 1994). In this viewpoint, subjective values of options are not necessarily calculated to make a decision. Instead, decision-making may involve the application of simple rules or principles to the decision situation, which minimizes the effort to make a decision. For instance, individuals may rely on simple heuristics, or rules of thumb, in response to the decision environment. Individuals may have a toolbox of simple heuristics that are often one-attribute judgments, which involves considering only the most important attribute without having to make any tradeoffs (Gigerenzer and Todd, 1999). Additionally, individuals may make decisions based on norms or conventions housed within their own social identity (March, 1994).

Another viewpoint is that people construct their preferences, but preferences are not necessarily well-defined or stable. Two central tenets of the constructed preference view is: 1) individuals do not just simply refer to a master list of preferences from memory, and 2) preferences are not necessarily generated by applying some task invariant algorithm of utility (Bettman, Luce, and Payne, 1998). Instead, how an individual makes a decision may be contingent upon a variety of factors and characteristics related to the decision environment. These factors may differentially highlight specific attributes of the decision environment and may also evoke different processing for combining information (Mellers, Schwartz, and

Cooke, 1998). Thus, preferences and the processes leading to preferences may be highly sensitive to the decision environment.

The constructed preference view of decision making has been around in psychology for many years (Tversky, Sattath, and Slovic, 1988; Slovic, 1995; Bettman, Luce, and Payne, 1998; Warren, McGraw, and Van Boven, 2011). Moreover, a considerable amount of research has identified a variety of task factors (e.g., numbers of alternatives, time pressure, the way in which preferences were elicited), and context factors (e.g., range of options, similarity among alternatives) that affect how preferences are constructed (for reviews, see Payne, Bettman and Johnson, 1993; Mellers, Schwartz, and Cooke, 1998; Warren, McGraw, and Van Boven, 2011). However, many studies have relied on choice or outcome data to explain construction processes, which at times makes it difficult to distinguish the different construction processes that lead to the choice. Some researchers have adopted process tracing methods, such as information boards and mouselab, to observe the order in which subjects search and acquire information during a decision task (e.g., Bigg et al., 1985; Billings and Marcus, 1983; Payne, Bettman and Johnson, 1988). But, these early process measures require subjects to either position a mouse over different windows or turn over all for information and so, may not always provide the most natural decision environment (Lohse and Johnson, 1996).

Here, in this dissertation, I take on the view that preferences are constructed, and that preferences are often influenced by the circumstances of the decision environment. Crucially, this dissertation brings new techniques to uncover the construction processes that lead to preferences. A main strategy of this dissertation is to use eye-tracking to extract more fine-grained process data to uncover the different strategies that individuals may employ in

response to changes in the decision environment. Eye-tracking provides a more natural measure of visual attention by monitoring eye position and movement without imposing additional requirements on subjects to obtain or maintain information. The first two studies in this dissertation use eye-tracking to further elucidate how people acquire information to construct their preferences in two specific contexts.

Additionally, in this dissertation, we explore constructed preferences on a neural level and use functional magnetic resonance imaging (fMRI) to measure brain activity and multi-voxel pattern analysis (MVPA) to further understand how these responses to different task demands are processed in the brain. Previous studies using traditional univariate methods have implicated a set of regions in the parietal and frontal cortices, often coined as the multiple-demand network, responding in a non-specific manner to general cognitive demands (Duncan and Owen, 2000; Fedorenko, Duncan, Kanwisher, 2013). However, we investigate neural activity at a finer-grained level and use MVPA to test whether the different responses to different forms of task complexity can be distinguished in these regions, which would go against previous studies suggesting that these regions serve as a general demand network. More importantly, the ability to distinguish on neural level may then prove fruitful in identifying and furthering our understanding of the neural and cognitive processes underlying different decision strategies and in turn, the processes that lead to our preferences during decision making.

## **Research Overview**

In chapter 2, I revisit a classic example of how preferences change in response to changes in choice situation and use eye-tracking to better explain this behavioral phenomena.

In this classic example, people exhibit systematic preference between choices and bids. For two gambles matched in expected value, people systematically chose the higher probability option but provided a higher bid for the option that offered the greater payoff. Different studies attribute preference reversals to changes in how attributes are weighted (Tversky, Sattath, and Slovic, 1988), changes in how attributes are combined to form an evaluation (Mellers, Ordonez, and Birnbaum, 1992), or changes in how a formed evaluation is expressed in different tasks (Goldstein and Einhorn, 1987). In our study, we replicated the classic behavioral effect, and our subjects demonstrated a robust preference reversal effect in the predicted direction. Even more critically, we found that preference reversals were accompanied by a shift in fixations on the two attributes, with people fixating on probabilities more during choices and on amount more during bids. Our results support that preference reversals may be due to changes in attribute weights. Additionally, using a natural measure of visual attention, our results suggest that the construction of preferences during decision making depends partly on task context because our tasks differentially directs attention at the two attributes.

In chapter 3, I describe another eye-tracking study that explored decision-making under a different type of task effect, changes in task complexity. This study highlights how eye-tracking can be especially useful in detecting subtle changes in decision strategies. In this study, we investigated how people make decisions on gambles in response to increases in the number of options and added time pressure. A number of different strategies have been proposed in trying to explain how people make decisions in response to these increases in complexity. However, past studies have mainly relied on behavioral choice data and coarse-grained process measures (e.g., mouselab; Lohse and Johnson, 1996) that may not have the

sensitivity to pick up intricacies of a decision strategy in these complex situations. Our results suggested that all of our subjects reduced the option set based on probability, eliminating options with lower probability. However, subjects not experiencing time pressure were then more likely to evaluate both the probability of winning and the payoff from the remaining option set, while those experiencing time pressure were more likely to then only evaluate the payoff from the remaining options. By using eye-tracking, we were able to find subtle and dynamic shifts in strategies in response to increasing complexities in our tasks. Our study also demonstrated novel ways of analyzing eye-tracking to further understand how decisions are made.

In chapter 4, I describe an fMRI study in which we investigate the neural responses to different manipulations of task complexity. In chapter 3, we found subtle differences in decision strategies in response to task complexity. In this study, we investigated the neural signatures of these different strategies in response to task complexity. Consistent with previous findings, our results showed widespread activation across regions that have been implicated as general demand areas (e.g. dmPFC, SMA, parietal cortices, insula, dlPFC). However, inconsistent with a general or non-specific role in cognitive demand, multi-voxel pattern analysis can distinguish different forms of task complexity in all of these regions. These results extended our understanding of how responses to different manipulations of complexity are represented in the brain and suggests that fMRI could potentially be used to decode or predict the difficulty manipulation from activity. An important next step would then attempt to decode and predict the specific strategy used in a particular decision situation.



CHAPTER 2 – Preference reversals in decision making under risk are accompanied by changes in attention to different attributes

Kim, B., Seligman, D., and Kable, J.W. (2012). *Frontiers in Decision Neuroscience*, 6(109)

### **Abstract**

Recent work has shown that visual fixations reflect and influence trial-to-trial variability in people's preferences between goods. Here we extend this principle to attribute weights during decision making under risk. We measured eye movements while people chose between two risky gambles or bid on a single gamble. Consistent with previous work, we found that people exhibited systematic preference reversals between choices and bids. For two gambles matched in expected value, people systematically chose the higher-probability option but provided a higher bid for the option that offered the greater amount to win. This effect was accompanied by a shift in fixations of the two attributes, with people fixating on probabilities more during choices and on amounts more during bids. Our results suggest that the construction of value during decision making under risk depends on task context partly because the task differentially directs attention at probabilities versus amounts. Since recent work demonstrates that neural correlates of value vary with visual fixations, our results also suggest testable hypotheses regarding how task context modulates the neural computation of value to generate preference reversals.

### **Introduction**

A challenge for theories of decision making under risk is to account for known systematic inconsistencies in people's decisions. An example is the "preference reversal phenomenon," which involves systematic inconsistencies between preferences and prices

(Lichtenstein and Slovic, 1971; Lichtenstein and Slovic 1973; Grether and Plott, 1979).

Preference reversals were initially demonstrated by Lichtenstein and Slovic (1971). When given a choice between two gambles of similar expected value, one with a high probability of winning a smaller amount of money (termed the *P-bet*) and another with a low probability of winning a larger amount (termed the *\$-bet*), most people choose the higher probability P-bet. However, when providing selling prices for the same exact gambles, most people assign a higher price to the larger amount \$-bet. These two decisions appear to be mutually inconsistent. The P-bet cannot be simultaneously better than *and* worse than the \$-bet, and one would expect people to demand a higher price for their preferred gamble. Preference reversals violate the principle of *procedure invariance*, whereby preferences should not change depending on how they are measured (Tversky, Slovic, and Kahneman, 1990; Stalmeier, Wakker, and Bezembinder, 1997).

Despite its apparent irrationality, the preference reversal phenomenon is remarkably robust. For specifically designed alternatives, the frequency of reversals can be greater than 50% (Lichtenstein and Slovic, 1973; Grether and Plott, 1979; Tversky, Slovic, and Kahneman, 1990). The basic inconsistency has been replicated numerous times by psychologists and experimental economists, including under different designs using non-gamble stimuli and various incentive mechanisms (Mowen and Gentry, 1980; Tversky, Slovic, and Kahneman, 1990; Mellers, Ordóñez, and Birnbaum, 1992; Mellers, Chang, Birnbaum, and Ordóñez, 1992). Further, preference reversals persist in the face of large incentives (Grether and Plott, 1979; Lichtenstein and Slovic, 1973), including when the experimenter exploits the inconsistency to take money from the subject (Chu and Chu, 1990; Berg, Dickhaut, and O'Brien, 1985).

Various explanations have been proposed for preference reversals, which attribute the reversal to changes at different stages of the decision process. Different theories attribute preference reversals to changes in how attributes are weighted (Tversky, Sattath, and Slovic, 1988), changes in how weighted attributes are combined to form an evaluation (e.g., additive versus multiplicative combination; Mellers, Ordóñez, and Birnbaum, 1992), or changes in how a formed evaluation is expressed, or translated into a response, in different tasks (Goldstein and Einhorn, 1987). Though conceptually distinct, changes at these different stages are also not mutually exclusive.

A prominent explanation for preference reversals is Tversky, Sattath and Slovic's (1988) *contingent weighting* hypothesis. They argue that attribute weights are closer to lexicographic (i.e., closer to all-or-none) in choice compared to other tasks, which leads to the most important attribute being weighted even more heavily in choice, a phenomena called the *prominence effect* (Slovic, 1975; Tversky, Sattath, and Slovic, 1988). Since most people are risk-averse (Holt and Laury, 2002), weighting probability more than amount, this would lead to the probability dimension being weighted even more in choice than other decision tasks. (Note there is some debate, though, about whether the prominence effect occurs for gambles; see Tversky, Sattath and Slovic, 1998, p. 382). By contrast, Tversky, Sattath and Slovic (1988) argue that the payoff dimension is weighted more during bids because of the *compatibility effect*, whereby attributes that are compatible with the output are given more weight (in this case, payoff is compatible with bids, since both are in dollars; Slovic, Griffin, and Tversky, 1988; Tversky, Sattath, and Slovic, 1988). Formally, Tversky, Sattath and Slovic (1988) model the change in responses across the two tasks as a change in the weight  $a_i$

(where  $i$  = choice, bid) of the following utility function for a gamble to win amount  $a$  with probability  $p$ :

$$U(p,a) = \log p + \alpha_i \log a$$

Note that this is simply the logarithmic transform of an expected utility model in which the degree of risk aversion varies between choices and bids.

Here, using visual fixations as an index of information processing and visual attention, we sought to determine what information people attend to during a preference reversal paradigm. Specifically, we aimed to test whether visual fixations reflect changes in the weighting of different attributes, with people looking at probability information more during choices and amount information more during bids. Since preference reversals could be due to changes at different stages of the decision process, this finding would also provide additional support for contingent weighting being at least part of the explanation.

This experiment also builds on recent research linking visual fixations and preferences. Rangel and colleagues have shown that visual fixations both reflect and influence preferences between goods (Armel, Beaumel, and Rangel, 2008; Krajbich, Camerer, Ledyard, and Rangel, 2009; Krajbich, Armel, and Rangel, 2010). Visual fixations also modulate the neural correlates of preferences, with activity in ventromedial prefrontal cortex and ventral striatum reflecting the value of the fixated item compared to the value of item not fixated (Lim, O'Doherty, and Rangel, 2011). Here we test whether the link between fixations and preferences generalizes to decision making under risk, and whether fixations are further linked to attribute weights. Given the link between fixations and neural correlates

of preferences, this evidence should also inform theorizing regarding the specific neural signals that might be modulated by task context to give rise to preference reversals.

Our investigation follows previous process tracing studies by Johnson and colleagues (Johnson, Payne, and Bettman, 1989; Schkade and Johnson, 1988). Using Mouselab, they found that individuals spent proportionally more time looking at probability information during choices than during bidding. However, Mouselab may not always provide the most natural decision environment (Lohse and Johnson, 1996). In Mouselab, subjects acquire information by positioning a mouse cursor over different windows, and the pattern of mouse movements is recorded. This can increase the amount of effort needed to acquire information, which can then alter the information processing behavior of subjects (Lohse and Johnson, 1996). Eye-tracking does not have this problem. Since eye-tracking does not impose additional requirements on subjects to obtain or maintain information, it might in some cases provide a more sensitive or more accurate measure of information processing. For this reason, as well as to build on recent work linking visual fixations and preferences, we thought it was important to further investigate preference reversals using eye-tracking techniques.

## **Materials and methods**

### **Participants**

Twenty-six paid volunteers from the University of Pennsylvania community participated in this study. Data from two participants were discarded because their responses suggested confusion regarding the bidding task. One participant's bids were not positively correlated with expected value, and the other participant bid higher than the amount to win in several gambles. The mean age of our final sample ( $N = 24$ ) was 23.6 years (age range: 19 -

29 years), and 52% were female. All participants gave written informed consent in accordance with the procedures of the Institutional Review Board at the University of Pennsylvania.

### **Tasks and stimuli**

On each trial, subjects either made a choice between two gambles (choice trials) or provided their evaluation of a single gamble (bid trials, see Figure 1). On choice trials, subjects chose between two different gambles with varying probabilities (12%-95%) of winning different amounts of money (\$10-\$98). On bid trials, subjects entered their subjective evaluation of a gamble in dollar amounts. At the end of each session, one trial was randomly selected, and participants were paid according to their decision on that trial. If subjects won money, they received that money in addition to the show-up fee of \$10.

We used E-Prime to present all behavioral stimuli (Psychology Software Tools, Pittsburgh, PA). Subjects entered their responses using a keyboard. Subjects were presented with a total of 100 bid trials and 100 choice trials in eight alternating blocks of 25 trials each. In case placement of the probabilities and amounts biased decision-making, half the subjects saw the amounts as the top number and the other half saw the probabilities as the top number. All subjects saw the same set of gambles in the same order. During a choice trial, subjects were presented with a screen with the word “Choose” for one second. They then saw a screen with two gambles side-by-side and had unlimited time to choose between the two gambles. Subjects pressed “1” to choose the gamble on the left side of the screen and pressed “0” to choose the gamble on the right. During a bid trial, subjects were presented with a screen with the word “Bid” for one second. They then saw a screen with a single gamble and had unlimited time to enter their dollar bid. Subjects used the number keys to enter their bid and

submitted their response by pressing the “return” key. Once bids were entered, subjects were unable to change their responses. Participants were instructed to bid the “smallest amount of money [they] would be willing to exchange for the opportunity to play the gamble.”

Subjects went through a training period in the beginning to ensure understanding of the task. Subjects had two practice trials for each of the trial types. On bid practice trials, subjects were taken through a series of questions after they entered their bid. These questions were used during training to ensure that subjects understood the bidding task and could provide well-calibrated bids. First, subjects were asked if they would forego playing out the gamble to take a counteroffer that was \$1 higher than their bid. If they answered “no,” they were told they bid too low and were asked to bid again. If subjects answered “yes,” they were then asked if they would play out the gamble and forego taking a counteroffer \$1 less than their bid. If they answered “no,” they were told they bid too high and were asked to bid again. Subjects repeated this process until they answered yes to both questions. These questions were only asked on practice trials, and were not included on experimental trials.

In choice trials, one gamble had a high probability of winning a small amount of money (termed the P-bet, e.g., 84% chance of \$20), and the other had a low probability of winning a larger amount (termed the \$-bet, e.g., 24% chance of \$70). Fifty pairs of P-bets (ranging from a 70-95% chance of winning \$10-\$34) and \$-bets (ranging from a 12%-37% chance of winning \$35-\$98) were selected so that the P-bet and \$-bet were approximately equal in expected value (EV), with differences ranging from \$0.00 to \$0.09 and a median difference of \$0.02. Probability ranges were chosen based on previous studies (e.g., Lichtenstein and Slovic, 1971) and ensured the ranges for P-bets and \$-bets did not overlap. See Table 1 for a list of gamble pairs. Amounts were chosen to provide a reasonable range of

expected values, given that subjects would be paid according to the outcome on a single trial. No probability or dollar amount was used more than twice in the stimulus set. This stimulus set was pre-tested in pilot behavioral subjects ( $n = 12$ ) who demonstrated a robust preference reversal effect, and has now been used in several studies in our laboratory. To encourage participants to attend to each choice and avoid following a simple heuristic (such as always choosing the higher probability gamble), ten of the fifty pairs were mismatched so that either the P-bet or \$-bet had a much higher EV. The EV across all gamble pairs varied from \$8.10 to \$29.23, with a median of \$18.13. Each pair was presented twice during choice trials, with the left-right placement of the gambles switching between presentations. The same gambles used in the choice task were shown once individually in the bidding task. Thus for each subject we have 100 choice and 100 bid trials where the stimulus on the left of the screen is identical, and what differs is the presence of another gamble or the bid prompt on the right side of the screen.

Both tasks were administered in an incentive compatible manner. At the end of the experiment, participants rolled dice to randomly determine one bid or choice trial to be played out for real money. If a choice trial was selected, participants were given the opportunity to play the gamble that they chose, using a 100-sided die to determine the outcome. For example, if the chosen gamble was a 75% chance of winning \$21, a roll of 75 or below on the die would pay \$21 and a roll of 76 or above would pay \$0. If a bid trial was selected, participants were paid using the Becker-DeGroot-Marschak (BDM) method, a widely used incentive-compatible procedure (Becker, Degroot, and Marschak, 1964). The subject's bid on the selected gamble was compared to a randomly generated counteroffer (between \$0 and the amount to win), created by dividing the roll of a 100-sided die by 100



and multiplying the resulting fraction by the amount to win. If the subject's bid was higher than the counteroffer, the subject played the gamble. If the subject's bid was lower than the counteroffer, the subject received the counteroffer amount. This method incentivizes participants to bid their true valuation of the gamble, the amount at which they would be indifferent between receiving their bid and playing the gamble. The amount of money subjects won varied from \$0 to \$37.41 with a median of \$21.

### **Eye-tracking**

We used an Eyelink II head-mounted eye-tracker (SR Research Ltd., Mississauga, Ontario, Canada) to monitor participants' eye movements during the task. A camera imaged the participant's right eye at 250 Hz. Subjects sat approximately 18 inches from the screen and were calibrated using a 9-point calibration. To manage eye drift and head movement, the subject fixated on a black dot at the center of the screen after each trial and a drift correction measured how much each subject's measured gaze differed from the center of the screen. The experimenter monitored drift corrections throughout the whole experimental session and re-calibrated when the subject's gaze drifted from the center. Eye-movements were recorded during each trial between the time of the first stimuli and the time of the subject's response.

### **Behavioral analysis**

We used Matlab (Mathworks, Natick, MA) and SPSS (SPSS Inc., Chicago, IL) to analyze our behavioral and eye-tracking data. For each pair of gambles, we categorized responses in the choice task according to whether the subjects chose the P-bet both times ("chose P"), chose each bet once ("chose =") or chose the \$-bet both times ("chose \$"). Participants were consistent about 79% of the time, choosing the same gamble across both

choices. In the bid task, we categorized responses according to whether the subject bid higher on the P-bet (“bid P”), bid equal amounts for both bets (“bid =”) or bid higher on the \$-bet (“bid \$”). Within the forty gamble pairs matched in expected value, we calculated two measures of the preference reversal effect. One measure included all instances of increasing preference for the \$-bet (“weak P-to-\$ reversals”), that is, when subjects chose the P-bet both times then bid equal amounts, when they chose each bet once then bid higher on the \$-bet, or when they chose the P-bet both times then bid higher on the \$-bet. The other measure included only this last category, instances where the subject chose the P-bet twice and then bid higher on the \$-bet (“strict P-to-\$ reversals”). We also calculated two similar measures for reversals in the unpredicted direction, from the \$-bet in choice to the P-bet in bids.

In addition, we estimated a model in both tasks that assumed subjects’ decisions were a function of the expected utility ( $EU$ ) of the gambles:

$$EU(p, a) = p \times a^{\alpha_i}$$

Here  $\alpha_i$  (where  $i$  = choice, bid) is a measure of risk aversion. An  $\alpha_i$  equal to one leads to risk neutral decisions, an  $\alpha_i$  less than one to risk averse decisions, and an  $\alpha_i$  greater than one to risk seeking decisions. As mentioned in the introduction, one simple model of contingent weighting is merely the logarithmic transform of this equation (Tversky, Sattath, and Slovic 1988). From that perspective, an  $\alpha_i$  equal to one means equal weighting, an  $\alpha_i$  less than one means probability is weighted more strongly, and an  $\alpha_i$  greater than one means amount to win is weighted more strongly.

For choices, we fit a logistic regression that assumed choice probabilities ( $cp$ ) were a function of the difference in expected utility between the two gambles:

$$cp(EU_1, EU_2) = \frac{1}{1 + e^{\beta(EU_1 - EU_2)}}$$

We fit this equation for each subject to his/her observed choices using an iterative optimization in MATLAB (fminsearch and fminunc) to find the maximum likelihood estimate of  $\alpha_{choice}$  and  $b$ . The  $\alpha_{choice}$ 's of two subjects exceeded the boundaries that our model could reliably estimate ( $0.17 < \alpha_{choice} < 5.05$ ), so we excluded both  $\alpha$ 's from these subjects from further analysis. For bids, we fit a model that assumed the subject's bid was equal to the expected utility of the gamble, using non-linear least squares in MATLAB. We obtained almost identical results to those reported below if we fit  $\alpha_{choice}$  and  $\alpha_{bid}$  using the logarithmic transform of expected utility (i.e., the contingent weighting equation in the introduction).

Response time was calculated as starting from the onset of the stimuli and ending when the participant submitted their responses.

Placement of the amounts and probabilities did not have any significant effects on choice and bidding behavior (i.e., strict or weak P-to-\$ reversals,  $\alpha_{choice}$  or  $\alpha_{bid}$ ). All  $ps > .10$ .

### **Eye tracking analysis**

We used Data Viewer (SR Research Ltd., Mississauga, Ontario, Canada) for all pre-processing of the eye-tracking data and Matlab (Mathworks, Natick, MA) for all eye-tracking analysis. The Eye-link II software automatically parses eye movement data into fixations, blinks, and saccades based on standard saccade thresholds (velocity threshold =  $30^\circ/\text{s}$ , acceleration threshold =  $8000^\circ/\text{s}^2$ ). Only fixations initiated after the onset of the gambles were included in our analyses. Additionally, the EyeLink on-line parser denoted a blink when the pupil was very small, or when the eye-camera image of the pupil was missing or severely distorted by eyelid occlusion.

We defined regions of interest (ROI) corresponding to each amount and probability within each trial. The size of the screen was 800 by 1200 pixels, and each ROI was

approximately 280 by 320 pixels. There were four ROIs in choice trials, and two ROIs during bid trials. For a controlled comparison between choice and bid trials, we focused our analyses on only the two ROIs for the left gamble in choice trials, since these were visually identical to and contained the same amount of physical space as the two ROIs in bid trials. For fixations and looking durations (but not first fixations), we observed the same pattern of results if we collapsed across all four ROIs in choice trials.

We included three dependent variables in our eye-tracking analyses: number of fixations, looking duration, and the first fixation of each trial. For each of our dependent variables, we ran an ANOVA with gamble type (P-bets versus \$-bets), attribute (probability versus amount), and trial type (choice versus bids) as within-subject factors and attribute placement (probability on top versus amount on top) as a between-subject factor. We refer to this ANOVA below as our between-task analysis. To test subsequent comparisons within a trial type, we ran separate ANOVAs for choice trials and bid trials with gamble type (P-bets versus \$-bets) and attribute (probability versus amount) as within-subject factors and attribute placement (probability on top versus amount on top) as a between-subject factor. We refer to these ANOVAs below as within-task analyses. These analyses were all done using raw fixation numbers and looking times, but we observed the same pattern of results if we examined ratios of these variables (e.g., the ratio of fixations on probability versus amount, etc.). Fixations and looking durations for gamble types and attribute were highly correlated. All  $r_s > .92$ ,  $p_s < .001$ .

For fixations and looking durations (but not first fixations), placement of the amounts and probabilities did not interact with the eye tracking effects reported below. There was, however, an interaction between attribute and attribute placement for all three dependent

measures. Subjects had more total fixations (mean =  $5.69 \pm 0.46$  fixations versus mean  $4.77 \pm .48$  fixations;  $F(1, 22) = 33.37, p < .001$ ), longer looking durations (mean =  $1,718 \pm 208$  ms versus mean =  $1,337 \pm 192$  ms;  $F(1, 22) = 22.15, p < .001$ ), and more first fixations (mean =  $77 \pm 3\%$  versus mean =  $23 \pm 3\%$ ;  $F(1, 22) = 87.54, p < .001$ ) for the attribute that was presented on top.

Finally, to test for any effects of individual differences, we looked at the correlation between each of our eye-tracking dependent variables (proportion of total fixations and looking duration by trial type and gamble type; proportion of total fixations, looking duration, and first fixations by trial type and attribute) and each of our behavioral variables (number of strict and weak P-to-\$ reversals,  $\alpha_{choice}$  and  $\alpha_{bid}$ ). This analysis excluded the two subjects whose choice alphas exceeded the boundaries that we could reliably estimate (these two subjects were also outliers in terms of the number of reversals, with neither making any weak P-to-\$ reversals while the minimum among the remaining subjects was 22 weak reversals).

## Results

### Behavioral Results

Overall, subjects spent more time on bid trials than on choice trials. There was a significant increase in response times from choice trials to bid trials,  $F(1,23) = 74.95, p < .001$ . The average response time was  $4,257 \pm 549$  ms during choice trials and  $6,894 \pm 485$  ms during bid trials. (Note that, presumably secondary to this reaction time effect, there were also more total fixations,  $F(1,22) = 43.57, p < .001$ , and longer looking durations,  $F(1,22) = 40.45, p < .001$ , during bid trials than during choice trials.) Within bid trials, subjects took longer to bid on \$-bets than on P-bets,  $F(1,23) = 31.43, p < .001$ . The average response time

for bids on P-bets was  $6,381 \pm 97$  ms and the average response time for \$-bets  $7,394 \pm 101$  ms.

Subjects also demonstrated a robust preference reversal effect. During choice trials, subjects chose the P-bet significantly more often than the \$-bet,  $F(1,23) = 34.02, p < .001$ . On average, subjects chose the P-bet both times for  $66 \pm 13\%$  of the pairs, chose equally for  $21 \pm 4\%$  of the pairs and chose the \$-bet both times for  $13 \pm 3\%$  of the pairs (see Figure 2a). In contrast, subjects bid significantly higher on the \$-bet than on the P-bet,  $F(1,23) = 18.22, p < .001$ . Subjects bid higher on the \$-bet for  $61 \pm 13\%$  of the pairs, bid the same on both gambles for  $10 \pm 2\%$  of the pairs, and bid higher on the P-bet for  $28 \pm 6\%$  of the pairs (See Figure 2b). Subjects preferred the P-bet significantly more often when choosing than when bidding,  $F(1,23) = 40.54, p < .001$ , and preferred the \$-bet significantly less often when choosing than when bidding,  $F(1,23) = 49.21, p < .001$ .

Across all gamble pairs, subjects exhibited increased preference for the \$-bet in bids more often than the reverse effect,  $F(1,23) = 104.37, p < .001$ . Subjects made weak P-to-\$ reversals for  $67 \pm 5\%$  of gamble pairs and weak \$-to-P reversals for  $10 \pm 3\%$  of gamble pairs. Subjects also exhibited significantly more strict P-to-\$ reversals, choosing the P-bet both times and bidding higher on the \$-bet, than strict \$-to-P reversals, choosing the \$-bet both times and bidding higher on the P-bet,  $F(1,23) = 53.30, p < .001$ . Subjects made strict P-to-\$ reversals for  $37 \pm 4\%$  of gamble pairs and strict \$-to-P reversals for less than  $1 \pm 1\%$  of gamble pairs. For pairs where the subject chose the P-bet both times, they bid an average of  $\$10.37 \pm 2.35$  higher on \$-bet.

Preference reversals were also evident by changes in risk aversion, or attribute weighting, in the two tasks. Subjects were risk-averse, weighting probability more, during

choice trials ( $a_{choice} = 0.77$ ,  $se = \pm .05$ ). In contrast, subjects were close to risk-neutral, weighting probability and amount almost equally, during bid trials ( $a_{bid} = 1.03$ ,  $se = \pm .01$ ; see Figure 2c and 2d).  $a_{choice}$ 's were significantly smaller than  $a_{bid}$ 's,  $t(21) = -4.37$ ,  $p < .001$ .

### Eye-tracking Results

For eye-tracking analyses, our main dependent variables were number of fixations and looking durations. Both of these variables showed strong effects of task context. In each task, subjects looked more at the preferred gamble type (P-bet in choices, \$-bet in bids) and the more heavily weighted attribute (probability in choices, amount to win in bids).

Subjects looked at the preferred gamble type more, fixating on P-bets more often during choice trials and \$-bets more often during bid trials (Figure 3). This was evidenced by a significant interaction between trial type and gamble type for both the number of fixations,  $F(1, 22) = 44.25$ ,  $p < .001$ , and for the duration of fixations,  $F(1, 22) = 23.53$ ,  $p < .001$ , in our between-task analysis. Looking within each task, subjects made significantly more fixations on P-bets (mean =  $8.73 \pm .55$ ) than on \$-bets (mean =  $7.55 \pm .61$ ) during choice trials,  $F(1, 22) = 27.48$ ,  $p < .001$ . Subjects also spent significantly more time looking at P-bets (mean =  $2,229 \pm 191$  ms) than at \$-bets (mean =  $2050 \pm 231$  ms) during choice trials,  $F(1, 22) = 7.77$ ,  $p = .01$ . In contrast, during bid trials, subjects made more fixations on \$-bets (mean =  $13.60 \pm .98$ ) than on P-bets (mean =  $12.05 \pm .93$ ;  $F(1, 22) = 22.75$ ,  $p < .001$ ) and spent more time looking at \$-bets (mean =  $4,213 \pm 445$  ms) than at P-bets (mean =  $3,727 \pm 405$  ms;  $F(1, 22) = 16.68$ ,  $p < .001$ ).

Fixations of the two attributes, probability and amount, also differed between choice and bid trials. Subjects were more likely to look at probabilities during choice and more likely to look at amounts during bidding (Figure 4). This was evidenced by a significant

attribute by trial type interaction for both number of fixations,  $F(1, 22) = 14.13, p < .01$ , and looking durations,  $F(1, 22) = 4.29, p < .05$ , in our between-task analysis. Looking within each task, subjects made significantly more fixations on probability (mean =  $4.3 \pm 0.32$  fixations) than on amount (mean =  $3.9 \pm 0.30$  fixations) during choice trials,  $F(1, 22) = 5.57, p < .05$ . Similarly, subjects spent marginally more time looking at probability (mean =  $1,126 \pm 122$  ms) than at amount (mean =  $1,012 \pm 100$  ms) during choice trials,  $F(1, 22) = 4.19, p = .05$  (This effect was more reliable when considering both gambles, instead of just the left gamble: duration on probability =  $2,121 \pm 233$  ms, duration on amount =  $1,865 \pm 191$  ms,  $F(1, 22) = 5.99, p < .05$ ). In contrast, during bid trials, subjects made significantly more fixations on amount (mean =  $6.74 \pm 0.53$  fixations) than on probability (mean =  $6.06 \pm 0.47$  fixations;  $F(1, 22) = 8.12, p < .01$ ), and spent marginally more time looking at amount (mean =  $2,137 \pm 220$  ms) than at probability (mean =  $1,832 \pm 237$  ms;  $F(1, 22) = 2.97, p < .10$ ).

Further, the difference in attribute fixations in the two trial types was more exaggerated for \$-bets than for P-bets. This was evidenced by a significant three way interaction between trial type, gamble type and attribute for both fixations,  $F(1, 22) = 5.43, p < .05$ , and for looking duration,  $F(1, 22) = 11.32, p < .01$ , in our between-task analysis.

We also examined which attribute was fixated on first in choice and bid trials. First fixations were more likely to be on probability than on amount across both kinds of trials (mean first fixation on probability =  $59 \pm 13\%$ ;  $F(1, 22) = 9.70, p < .01$  in our between-task analysis). Looking within each task, probability was more likely to be fixated on first in both choice trials,  $F(1, 22) = 11.06, p < .01$ , and in bid trials,  $F(1, 22) = 4.62, p < .05$ . This was qualified by a significant interaction between attribute and trial type ( $F(1, 22) = 5.88, p < .05$ ), with probability more likely to be fixated on first in choice trials ( $62 \pm 5\%$  in choice



trials versus  $55 \pm 8\%$  in bid trials). This interaction, however, was not reliable when we included both choice options (all four ROIs) in the analysis, rather than restricting our analysis to only the left choice option ( $F(1, 22) = 1.27, p > .10$ ). The two-way interaction between attribute and trial type was further qualified by a three-way interaction between attribute, trial type and attribute order,  $F(1, 22) = 52.32, p < .001$ , in our between-task analysis. This interaction arose because during bid trials, subjects primarily fixated on the top attribute first (mean =  $88 \pm 3\%$  of first fixations), regardless of whether it was probability or amount. Subjects fixated on the top attribute first to a lesser degree during choice trials ( $67 \pm 5\%$  of first fixations). Thus it appears attribute placement had a stronger effect on first fixations than attribute identity.

Finally, we tested for any effects of individual differences by examining the correlations between the eye-tracking measures and behavioral measures. Only two of these correlations were statistically significant. Individuals who fixated on the P-bet more during choice (evaluated using either fixations or looking duration) were more risk-averse,  $r_s = -.66$  and  $-.61, p_s < .001$ , respectively. Note these correlations remained significant even when using a Bonferroni correction for the number of correlations examined.

## **Discussion**

Here we replicated the preference reversal phenomenon in decision-making under risk, in which people facing two gambles of equal expected value choose the one with the higher probability of winning, but assign a higher price to the one with the larger potential payoff. We have additionally shown that preference reversals are accompanied by changes in visual fixations. Participants had more fixations on the preferred gamble in each task (P-bets in choices, \$-bets in bids). They also had more fixations on the more heavily weighted

attribute in each task (probability in choices, amounts in bids). These results show that visual fixations reflect preferences in decision making under risk, as they do in decisions about goods (Krajbich, et al, 2009; Krajbich, Armel and Rangel, 2010), and that fixations may further reflect attribute weights in a multi-attribute choice paradigm. These results support that contingent weighting is part of the explanation for preference reversals, and also suggest testable hypotheses about the neural mechanisms of preference reversals.

Behaviorally, we replicated the classic preference reversal finding. Our participants predominantly chose the high-probability bet from a pair of gambles matched in expected value, and predominantly assigned higher prices to the (alternative) bet that offered the larger amount to win. For 37% of gamble pairs, our participants made strict P-to-\$ reversals, choosing the P-bet twice and bidding higher on the \$-bet. Consistent with this, participants were overall risk-averse during choices, and very slightly risk-seeking during bids.

One novel aspect of our paradigm compared to previous work is the highly repeated nature of the trials. Participants made 100 choices and 100 bids over the course of the experiment. Our results demonstrate that preference reversals are not eliminated when subjects are tested with many repeated trials. Our design does not allow us to test whether they are diminished by repeated trials, though the effects we observed in this experiment are of similar size to those reported in the literature. Most neuroscientific methods require many repeated trials and within-subject comparisons. While many context effects are eliminated under these conditions, our results show that preference reversals are not, and therefore may be a good paradigm for neuroscientific studies of context effects.

Despite only having to assess the value of one gamble, participants took longer to make bids than to make choices. Although it is possible that the difference in response times

might be due to differences in response entry, it is unlikely that pressing one or two more buttons accounts for an increase of more than 2 seconds. Spending more time deciding on a bid than choosing between two options is consistent with previous findings (Schkade and Johnson 1988; Johnson, Payne, and Bettman 1989). It suggests that the decision process for assigning prices is potentially more complex than that required for binary choices (e.g., multiplicative for bids versus additive for some choices; See Mellers, Ordóñez, and Birnbaum, 1992). This is consistent with models that assume that binary choice is the more basic process (Johnson and Busemeyer, 2005), but not with models that assume pricing is more basic (Luce, Mellers, and Chang 1993). Pricing and matching tasks have rarely been studied in decision neuroscience (though see Plassmann, O’Doherty, and Rangel, 2007) so an interesting question for future research is the degree to which choice and bidding rely on shared versus distinct neural processes.

Recent work has found that fixations reflect trial-to-trial variability in preferences (Krajbich, et al, 2009; Krajbich, Armel and Rangel, 2010). Our findings extend this principle to decision making under risk. During choices, participants made more fixations on the preferred gamble type in that task, P-bets, and spent a greater amount of time looking at P-bets. During bids, participants made more fixations on the preferred gamble type in that task, \$-bets, and spent a greater amount of time looking at \$-bets. We acknowledge that the bidding results are confounded by a longer reaction time for \$-bets than for P-bets, making this finding more difficult to interpret. There is not such a confound in the choice results, however, which clearly replicate the link between fixations and preferences observed in other choice domains.

Our key finding, though, was that preference reversals were associated with changes in visual fixations to the two gamble attributes in the two tasks. During bidding, participants made more fixations on amounts and spent a greater amount of time looking at amounts. During choices, participants made a greater number of fixations on probabilities and spent a greater amount of time looking at probabilities.

The directionality of these results is broadly consistent with the contingent weighting hypothesis. According to this hypothesis, preference reversals may have resulted from increased weight on probability in value computations during choice, and corresponding increased weight on amount during bids. We found that people fixate probabilities more during choice and amounts more during bids. It is also possible that these fixation patterns may have also resulted from other processes than changes in attribute weights. Further research should explore other possible processes that may affect fixation patterns, such as changes in attribute spacing or similarities of the levels along an attribute (Mellers and Biagini, 1994), during the preference reversal phenomenon.

These differences in fixations might only be an index of the differential weighting of attributes, or alternatively might also be a cause of this differential weighting. This latter possibility raises several ideas for future research that would involve exogenously controlling fixations. If fixations influence attribute weighting, then preference reversals might be reduced, or even eliminated, when participants are forced to look equally at probabilities and amounts. In addition, forcing more fixations to the weaker attribute of an option might make people less likely to choose that option, a potential exception to previous work showing that fixating on an option makes people more likely to choose it (Armel, Beaumel, and Rangel, 2008).

However, a simple model in which preference reversals are due solely to changes in attribute weights, and fixations provide an unbiased index of these weights, has trouble completely accounting for our data. As shown in Figure 2d, participants' decisions reflect nearly equal weighting of probability and amount during bids (i.e., participants are close to risk neutral), and a greater weighting of probability during choices (i.e., participants are risk-averse). In contrast, as shown in Figure 4, participants fixate probabilities more during choices and amounts more during bids.

One possible resolution is that people are intrinsically risk-averse, weighting probabilities more, and only changes from that intrinsic baseline are reflected in changes from equal fixation of the two attributes. Another possibility is that fixations are monotonically, but not linearly, related to attribute weights. While participants are close to risk-neutral during bids, they are still significantly risk-seeking, and they also fixate amounts more than probabilities. A final possibility, of course, is that fixations and looking times reflect more than attribute weights alone. For example, first fixations showed a strong effect of the spatial position of attributes, and other influences could have shifted fixations similarly in both choices and bids.

Our findings are similar to those reported previously by Johnson and colleagues (Johnson, Payne, and Bettman, 1989; Lohse and Johnson, 1996). Using Mouselab, those authors found that subjects attended to amounts more, and probabilities less, during bids than during choices (for example, 56% versus 51% of the time in Experiment 1 of Schkade and Johnson, 1988). This same overall pattern was arguably more dramatic in our fixation data. This points to a potential difference in sensitivity between the two techniques, which might arise from how people process information differently in the two environments. In the

Mouselab environment, only one piece of information is available at any one time. Johnson and colleagues noted that in their experiments some subjects used a strategy of first looking at all of the information sequentially, and then holding it in mind while they made their decision. Under free viewing, subjects do not adopt this strategy at all. Of the total fixations in Figure 3,  $3.59 \pm .28$  fixations during choice trials are made when returning to an item after fixating on it once and then looking elsewhere, while  $5.40 \pm .42$  represent return fixations during bidding.

Our data on individual differences provide additional support for the notion that fixations reflect preferences during choices. Individuals who fixated more on the P-bet during choice trials were more risk-averse. However, we did not find any other significant correlations between individual differences in eye movements and behavioral measures. A possible reason for these null findings is that we have a small sample size for evaluating individual differences. Additionally, most participants show a robust preference reversal effect, so there is limited variability in the number of preference reversals. Future research could further explore how individual differences in fixations related to individual differences in preference reversals, perhaps using a larger sample or a paradigm in which there is greater variance in the behavioral effect.

Future research could also investigate how different presentation formats affect eye fixations and, in turn, preference reversals. For example, Johnson and colleagues (1988) have shown that different presentation formats can move around preference reversals and that these changes are associated with changes in information processing. Specifically, when probabilities are more complex (e.g., 399/456) the number of preference reversals increases. In addition, subjects spent a greater proportion of time viewing probability information when

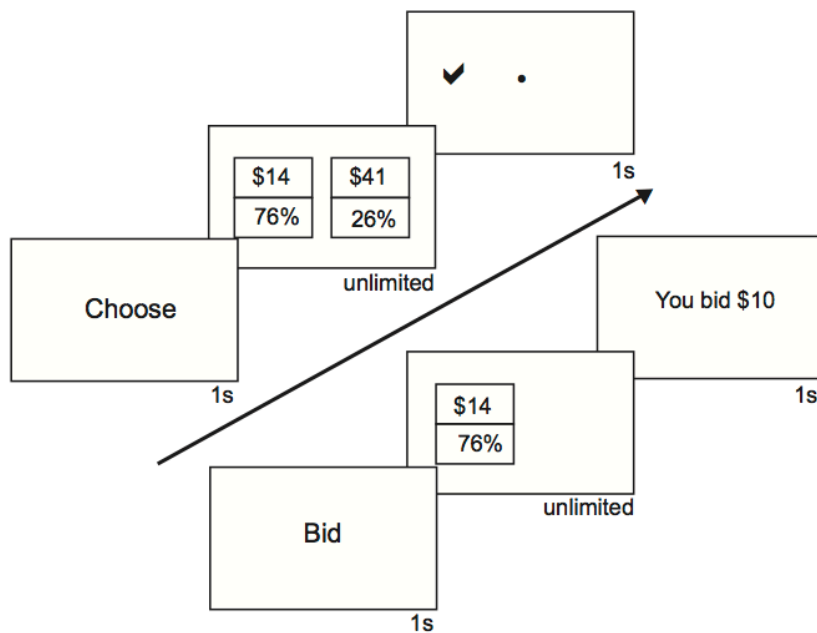
probabilities were displayed as hard fractions, and subjects who spent more time on probability also demonstrated more reversals. We do not know of any similar studies looking at the relationship between visual fixations and decisions under risk when presentation format varies, though this would be an interesting follow-up to our study.

Another interesting question for future research concerns the neural mechanism of preference reversals. Several studies have now demonstrated that neural activity in ventromedial prefrontal cortex and ventral striatum is correlated with the subjective value of the options under consideration during decision making (Kable and Glimcher, 2009). A recent study showed that value-related activity in these regions is further modulated by visual fixations, tracking the value of the fixated item compared to the item not fixated (Lim, O'Doherty, and Rangel, 2011). Paired with our findings, this suggests the intriguing hypothesis that neural activity in ventromedial prefrontal cortex and ventral striatum differentially reflects probabilities and amounts during choices and bids. That is, in a preference reversal paradigm, neural activity in these regions might be more strongly affected by probabilities during choice and more strongly affected by amounts during bids. Such a finding would also suggest that neural correlates of probability and magnitude (Knutson, Taylor, Kaufman, and Glover, 2005) could depend on the task context.

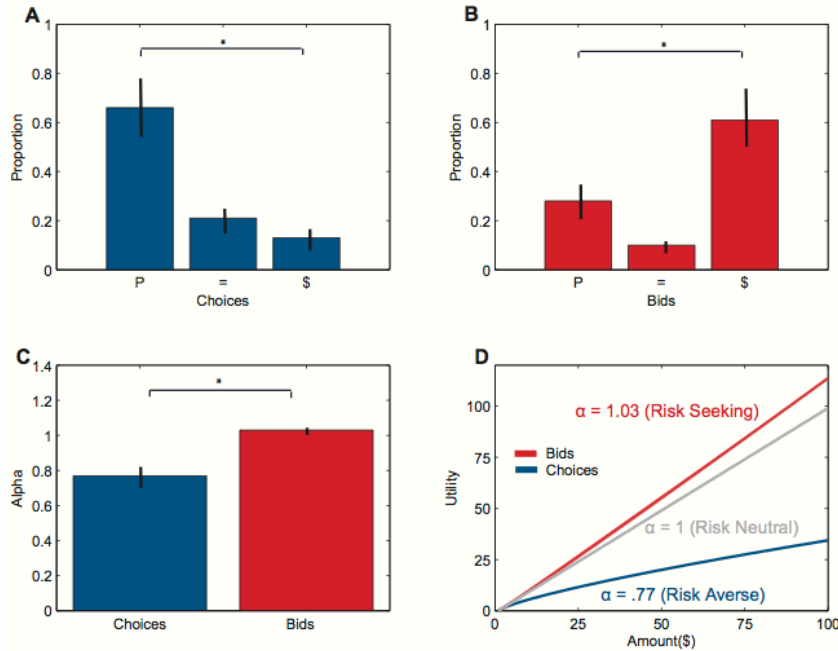
In conclusion, we found that preference reversals in decision making under risk were accompanied by differential attention to probabilities versus amounts. The directionality of this effect was consistent with a contingent weighting explanation (Tversky, Sattath, and Slovic, 1988), with people looking at probabilities more during choice and amounts more during bids. Given recent work demonstrating neural correlates of value (Kable and Glimcher, 2009), which are modulated by visual attention (Lim, O'Doherty, and Rangel,

2011), this work suggests testable hypotheses regarding how task-dependent strategies might alter the weighting of attributes in the neural computation of value to cause preference reversals.

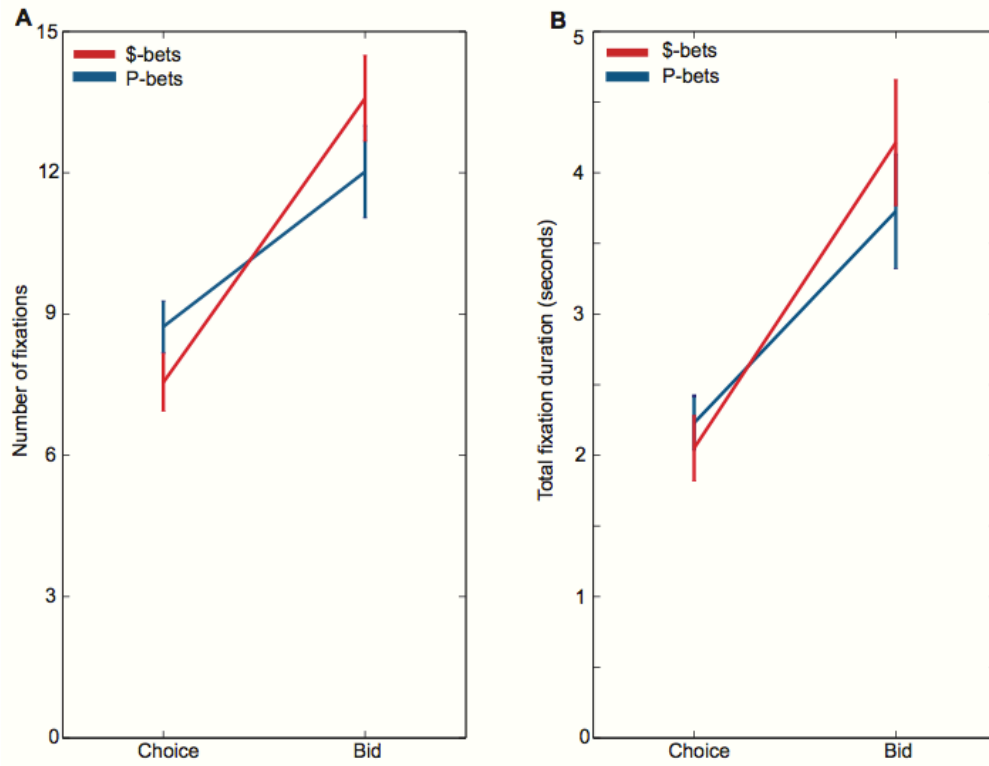




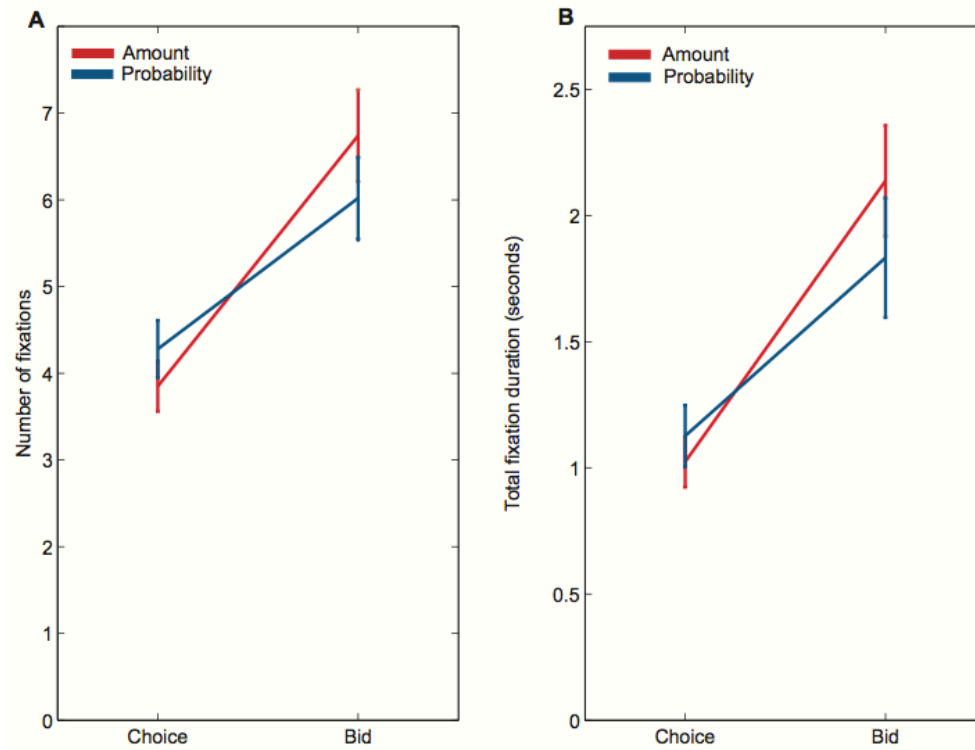
**Figure 1.** Choice and bid tasks. The sequences of events within a trial for both choice and bid trials are shown. For choice trials, subjects saw “Choose” for 1 second. Subjects then saw two gambles, a \$-bet gamble and a P-bet gamble. Subjects had unlimited time to choose one of the gambles. After submitting their response, subjects would see a check mark on the side of the chosen gamble. For bid trials, subjects saw “Bid” for 1 second. Subjects then saw one gamble, either a \$-bet or a P-bet gamble, on the left side of the screen. To the right of the gamble was a “\$” where subjects bids would appear. Subjects had unlimited time to submit their bids. After submitting their response, subjects would see the amount they bid.



**Figure 2.** (A) Percentage of gamble pairs where subjects chose the P-bet option twice (P), the \$-bet twice (\$), or both equally (=). On average, subjects chose the P-bet significantly more than the \$-bet. (B) Percentage of gamble pairs where subjects bid higher for the P-bet option (P), \$-bet option (\$), or bid the same amount for both gambles (=). On average, subjects bid higher on \$-bets than on the P-bets. (C) Average alpha values for choice trials and bid trials. Alphas were significantly higher for bidding than for choice. (D) The average expected utility function for bids and choices given the inferred alphas. Subjects were risk-averse during choices and slightly risk-seeking during bids.



**Figure 3.** (A) Average number of fixations of \$-bets and P-bets during choices and bids. (B) Average duration looking at \$-bets and P-bets during choices and bids.



**Figure 4.** (A) Average number of fixations of probabilities and amounts during choices and bids. (B) Average duration looking at probabilities and amounts during choices and bids.

**Table 1.** List of gamble pairs used during the task. Each pair was shown twice during choice trials. Each option was shown individually during bid trials.

\$-Bet Option		P-Bet Option	
Probability	Amount	Probability	Amount
12%	\$71	86%	\$ 10
19%	\$48	83%	\$11
14%	\$73	85%	\$12
15%	\$72	83%	\$13
23%	\$50	82%	\$14
17%	\$71	93%	\$13
16%	\$80	71%	\$18
14%	\$93	77%	\$17
29%	\$46	79%	\$17
18%	\$75	90%	\$15
20%	\$68	85%	\$16
16%	\$87	77%	\$18
32%	\$46	92%	\$16
19%	\$80	72%	\$21
17%	\$93	75%	\$21
24%	\$70	84%	\$20
26%	\$66	78%	\$22
27%	\$64	91%	\$19
29%	\$62	72%	\$25
21%	\$86	95%	\$19
28%	\$65	91%	\$20
22%	\$83	76%	\$24
33%	\$58	87%	\$22
33%	\$58	87%	\$22
25%	\$77	74%	\$26
20%	\$98	82%	\$24
21%	\$94	73%	\$27
22%	\$92	88%	\$23
23%	\$88	81%	\$25
30%	\$69	90%	\$23
30%	\$69	90%	\$23
26%	\$87	78%	\$29
33%	\$69	76%	\$30
36%	\$64	70%	\$33
24%	\$97	75%	\$31
31%	\$76	71%	\$33
35%	\$68	88%	\$27
37%	\$66	79%	\$31

32%	\$85	80%	\$34
18%	\$45	80%	\$30
15%	\$62	95%	\$26
31%	\$85	81%	\$12
13%	\$75	94%	\$28
34%	\$82	73%	\$14
27%	\$38	87%	\$32
30%	\$35	86%	\$34
37%	\$79	70%	\$15
25%	\$96	74%	\$11
28%	\$88	93%	\$10
37%	\$79	70%	\$15

## CHAPTER 3 – Simplifying strategies in response to increasing number of options and time pressure: Behavioral and eye-tracking evidence

### **Introduction**

While some decisions are simple, some can be quite complex. When making a simple decision between two or three alternatives with an unlimited amount of time, people tend to use a compensatory decision strategy, systematically processing all the relevant information. Compensatory strategies involve making tradeoffs, where a good value on one attribute can make up for, or compensate, for bad values on other attributes (Payne, Bettman, and Johnson, 1993). Thus, the decision maker chooses the option with the best overall value among the options, which often involves substantial computational processing of the information to make the decision. However, other decisions are complex and demanding due to factors like increasing the number of options or increasing time constraints, which amplifies the computational demands of the decision context (Payne, 1976; Shugan, 1980; Svenson and Edlan, 1987). When confronted with a more demanding decision-making situation, people tend to move away from compensatory strategies and instead, adopt simplifying strategies that are selective in the use of information (Payne, Bettman, and Johnson, 1993; Shah and Oppenheimer, 2008).

Here, we are less concerned with that fact that people simplify, and are more interested in tracing out how their simplifying strategy changes incrementally as difficulty increases. We think these incremental changes will elucidate why people simplify in the ways they do in different contexts. In motivating our study, we first review the past literature

identifying the many different types of decision strategies that have been suggested. We then discuss the Adaptive Decision Maker framework (Payne, Bettman and Johnson, 1993), which could serve as a comprehensive framework for strategy selection and explain the multitude of proposed strategies. Finally, we introduce the current study, focusing on how eye-tracking permits a more detailed test of the adaptive decision maker idea than could be done with behavior data alone.

### **A variety of simplifying strategies**

Previous research has identified many different types of simplifying strategies in response to increasing difficulty during decision making. These different simplifying strategies may reduce the amount of cognitive effort or computational demands, compared to what might be required by a compensatory strategy, when making a decision. Broadly speaking, these strategies can be categorized into two types of decision strategies: 1) non-compensatory strategies and 2) combination of compensatory and non-compensatory strategies.

First, a non-compensatory strategy often involves using heuristics or shortcuts to simplify the decision context. These strategies do not involve systematically going through all relevant information and involve using less computation processing of information than compensatory strategies. A key distinction of non-compensatory strategies is that these strategies do not involve making tradeoffs, so a good value on one attribute does not make up for bad values on other attributes (Payne, Bettman, and Johnson, 1993).

Several non-compensatory strategies have been proposed in response to increasing demands in the decision environment. For instance, a common non-compensatory strategy suggested in response to increasing number of options is a lexicographic strategy, which



involves only evaluating the most important attribute and ignoring others to reduce the amount of information processing needed to make a decision. The option that has the best value on that attribute is then selected (Payne, 1976; Payne, Bettman, and Johnson, 1993; Schram and Sonnemans, 2008). Similarly, an elimination-by-aspects strategy (EBA; Tversky, 1972) involves evaluating the most important attribute first and then eliminating options that fall below a cutoff level for that attribute. The EBA process continues with the second most important attribute, and so on, until one option remains. Additionally, another noncompensatory strategy suggested in response to increasing demand is satisficing (Simon, 1955, 1956; Schwartz et al., 2002; Glockner and Herbold, 2011). A satisficing strategy involves looking at the options one at a time until finding an option that reaches the threshold of acceptability and is “good enough.” This option is then chosen and the evaluation process is discontinued without looking at all the alternatives.

Second, a combination of compensatory and non-compensatory strategies involves using these different strategies at different phases of the decision process. These combination strategies may involve using a simple non-compensatory strategy to reduce the option set, but then use a more extensive compensatory strategy to choose among the remaining options (Payne, Bettman, and Johnson, 1993). Typically, a combination strategy may involve an initial phase, where options are eliminated based off a cutoff level for an attribute, similar to an EBA strategy. But instead of continuing on with a non-compensatory strategy, the second phase of a combination strategy involves using a compensatory strategy to select among the remaining options (Payne, 1976). Another example of a combination strategy is to initially reduce the option set based on spatial arrangement instead of attribute information and then search through that reduced subset to find the option with highest overall value (Reutskaja et

al., 2011). These strategies may involve more computational demand than strategies that rely solely on non-compensatory methods.

### **The adaptive decision maker reconsidered**

In sum, previous researchers have proposed many different simplifying strategies that people may use in response to increasing decision complexity. Yet, even as more strategies are uncovered, we still understand very little about why people engage in one strategy over another or why different strategies have been observed in response to similar decision demands.

In the *Adaptive Decision Maker*, Payne, Bettman, and Johnson (1993) put forth one of the earliest theoretical frameworks for why subjects engage in different decision strategies. They argue that strategy selection is based on an effort-accuracy framework where individuals adapt to a decision context by foregoing some accuracy to reduce effort. The basic idea is similar to the speed-accuracy tradeoff widely studied in perceptual psychophysics and cognitive psychology. Decision strategies vary in the cognitive effort required from the number of computational steps involved in reaching a selection and in accuracy—the likelihood that the selection made matches the one that would result if computational time were unlimited. Payne, Bettman, and Johnson (1993) illustrate the basic aspects of the theory using simulations. Two factors, however, have limited the amount of empirical data that have been brought to bear on this and other theories of strategy selection.

First, most studies have treated decision complexity or decision difficulty as a categorical factor (e.g., not difficult vs. difficult). However, the adaptive decision maker framework assumes the computation complexity of decision strategies varies on a continuum. In other words, simplifying strategies depend on the level of difficulty of the task. More

effortful task may elicit further simplifying strategies, like choosing based on one attribute of the options, while less effortful decision contexts will require less simplification of the task (e.g., satisficing). To really test this idea would require varying the difficulty of the decision context more continuously, to push decision-makers to different points on the computational complexity-accuracy tradeoff.

Second, and perhaps more importantly, we have lacked the techniques to detect and discriminate between decision strategies at the level of richness required to test for computation complexity-accuracy tradeoffs in detail. This shortcoming is in part because our process measures of decision-making are relatively coarse-grained, compared to the nuances of different decision strategies that need to be discriminated. Early process work involved using information boards and mouselab to observe the order in which subjects search and acquire information during a decision task (e.g., Bigg, et al., 1985; Billings and Marcus, 1983; Payne, Bettman and Johnson, 1988; Creyer, Bettman, and Payne, 1989). However, since Mouselab and information boards require subjects to either position a mouse over different windows or turn over a cell for information, these methods may not always provide the most natural decision environment (Lohse and Johnson, 1996). More recently, researchers have used eye tracking to understand how people acquire information and come to their judgments during decision-making tasks (e.g., Kuo et al., 2009; Reutskaja et al, 2011; Venkatraman et al, 2009; Gloeckner and Herbold, 2011; Kim, Seligman, and Kable 2012). Eye-tracking provides a more natural measure of visual attention by monitoring eye position and movements without imposing additional requirements on subjects to obtain or maintain information. Yet most previous eye-tracking studies have used relatively simple measures of what options people look at and how they search for information.

## **Overview of the current investigation**

The current investigation investigates how decision making changes as the demands of the decision environment increases. In line with previous work, we hypothesize that people will adopt a simplifying strategy as the demands of the decisions increases. Critically, our investigation aims to extend the adaptive decision maker framework by testing whether strategy selection in response to incremental increases in difficulty changes in a gradual rather than categorical manner. More specifically, we hypothesize that as the decision increases in difficulty, subjects will shift from a combined compensatory and non-compensatory strategy to a simpler non-compensatory strategy. In order to test this, we take two steps to enable more systematic examinations of computational complexity-accuracy tradeoffs in decision strategy selection. First, we vary decision difficulty in a more continuous rather than categorical fashion. Our task consists of simple gambles (e.g., 45% chance of winning \$30), and we vary decision difficulty in a couple of ways. The number of options varies, as subjects choose one gamble among 2, 4, 8 or 16 gambles, and time pressure varies, as some subjects experience time pressure and others do not. One trial is randomly played out for each subject, which therefore incentivizes the subject to choose a “good option” according to his or her preferences. Second, we try to extract as much information as possible from our behavioral and eye-tracking measures about what decision strategies subjects may be using. Our eye-tracking measures look separately at the different attributes within options, consider how search patterns change over the course of a trial, and examine the joint distributions of eye-tracking and behavioral data.

As we are able to show, it is possible to extract from eye-tracking measurements more fine-grained process data that speaks to the different strategies that individuals may

employ in the face of increasing decision difficulty. Specifically, we are able to test whether subjects are actually employing the previously proposed strategies. More importantly, we are also able to show that strategy selection in response to incremental increases in difficulty changes in a gradual rather than categorical manner, as originally proposed in the Adaptive Decision Maker (Payne, Bettman, and Johnson, 1993). At less extreme levels of difficulty, people use a combination strategy by using the available information (attribute levels, spatial position) to reduce the choice set and choose in a compensatory manner from the smaller reduced set (Payne, 1976; Reutskaja, 2011), while at more extreme levels of difficulty, this strategy shifts towards a noncompensatory elimination-by-aspects type of strategy (Tversky, 1972).

## **Method**

### **Participants and Procedures**

Sixty-eight paid volunteers from the University of Pennsylvania community participated in this study. Data from three participants were discarded due to technical malfunctions during the experiment, and data from one participant was excluded due to excessive head movement. The mean age of our final sample ( $n = 64$ ) was 23.8 years, and 52% were female. The subjects were split into two different timing conditions: 1) without time pressure (30 seconds time limit;  $n = 32$ ) and 2) with time pressure (10 seconds time limit;  $n = 32$ ). All participants gave written informed consent in accordance with the procedures of the human subjects review board at the University of Pennsylvania.

We used E-Prime to present the behavioral stimuli (Psychology Software Tools, Pittsburgh, PA). On each trial, subjects chose one option among different gambles with varying probabilities (7% - 99%) of winning different amounts of money (\$3 - \$200). The

complexity of the decision task varied with the number of options for each trial. The number of options varied over four levels: 2, 4, 8, and 16. See Figure 1a-d for examples of each trial type. At the end of each session, one trial was randomly selected, and participants played out the selected gamble from that trial. If subjects won the gamble, they would receive the monetary reward in addition to the show-up fee of \$10.

### **Stimuli Design**

The gambles in our task were constructed based on a simple compensatory model, expected utility (EU). The gambles in our experiment were all of the form where there was a probability,  $P$ , of winning an amount of money,  $A$ , and a probability  $(1-P)$  of winning nothing. The EU of each gamble in our experiment is then given by:

$$EU = P \cdot A^\alpha$$

Alpha ( $\alpha$ ) measures the curvature of the value function for gains and is the coefficient for risk-aversion. An alpha less than 1 is risk-averse, an alpha above 1 is risk-seeking, and an alpha equal to 1 is risk-neutral (choosing according to expected value). Although other compensatory models exist, of course (e.g., prospect theory), we chose expected utility because it was a simple one-parameter model.

We constructed the behavioral stimuli to have equal expected utility, assuming different alpha levels. Alpha levels ranged from 0.5 to 1.1, increasing in .10 increments. Each alpha level was also associated with four levels of average expected value (calculated by taking the mean of the expected value of all the options), to ensure that the range of expected values were similar throughout the task at each alpha level. The average expected values were \$9, \$10, \$11, and \$12. One gamble in each choice, which we call the “pop-out” option, had a higher expected utility than all the other options. Each alpha level was crossed

with 4 of 5 levels of pop-out: 20%, 40%, 60%, 80%, or 100% greater subjective value than all the other options within that trial. There were 28 trials for each option type leading to a total of 112 trials for the full task. All the gambles in the 8-, 4-, and 2-option trials were constructed from the 16-option trials, with the pop-out always included in all trial types. When we piloted the task, subjects ( $n = 10$ ) did not notice the repeat gambles. Subjects also had four training trials in the beginning to be acquainted with the task. Half the subjects saw the amounts on top and the other half saw the probabilities on top. All subjects in both timing conditions saw the same set of gambles.

### **Eye-tracking**

An Eyelink II head-mounted eye-tracker (SR Research Ltd., Mississauga, Ontario, Canada) monitored participants' eye movements during the task. Subjects were seated approximately 18 inches from the screen and were calibrated on a 9-point calibration. Between trials, a black dot would appear in the middle of the screen for subjects to fixate on in order to manage eye drift. This drift correction measured how much each subject's gaze and the central point differed over a short time period. The experimenter monitored the drift corrections at all times, and re-calibrated when the subject's gaze drifted from the center. The number of re-calibrations varied by subject. Eye movements were recorded, starting from the onset of the stimuli and ending when the participant submitted their responses. The Eyelink II software automatically parses eye movement data into fixations, blinks, and saccades based on standard saccade thresholds (velocity threshold =  $30^\circ/\text{s}$ , acceleration threshold =  $8000^\circ/\text{s}^2$ ). Only fixations initiated after the onset of the stimuli were included in our analyses. We defined regions of interest (ROI) corresponding to each amount and probability within each trial. The size of each ROI was approximately was 240 by 90 pixels.

### **Analytical strategy**

We used Data Viewer (SR Research Ltd., Mississauga, Ontario, Canada) for all pre-processing of the eye-tracking and Matlab (Mathworks, Natick, MA) and SPSS (SPSS Inc., Chicago, IL) to analyze our behavioral and eye-tracking data. We also used SAS (SAS Institute Inc., Cary, NC) to examine, in both the behavioral and eye-tracking measures, linear and non-linear changes in response to increases in the number of options. We estimated mixed linear models using the MIXED procedure in SAS, which allowed us to choose the appropriate covariance structures for each estimated model.

### **Behavioral analysis**

*Response times.* Response time was calculated as starting from the onset of the stimuli and ending when the participant submitted their responses to choose an option.

*Estimating alpha.* To calculate alphas, we fit a multinomial regression that assumed choice probabilities were a function of the difference in expected utility between each option and a reference option. We fit this equation for each subject to his/her observed choices using an iterative optimization in MATLAB (fminsearch and fminunc) to find the maximum likelihood estimate of alpha. Alpha values were estimated separately for each trial type.

*Choices.* We calculated the percentage of times the pop-out option was chosen, the percentage of times the option with the highest expected utility was chosen (given that subject's alpha), the percentage of time the highest probability option was chosen, and the percentage of time the highest amount option was chosen. We calculated these percentages for 2-, 4-, 8-, and 16-option trials separately.

### **Eye-tracking analysis**



*Proportion of options fully evaluated:* Options were considered “fully evaluated” if subjects looked at both the probability *and* the amount of the specific option.

*Proportion of fixations on each attribute:* We calculated the proportion of fixations on amount and the proportion of fixations on probability separately for each of the trial types.

*Fixation transitions:* We categorized eye fixation transitions into 3 groups based on the transition from the current fixation to the next fixation:

(1) **Within-attribute:** subjects looked at the same attribute in a different option as their next fixation. We further categorized these transitions into scanning over probability or scanning over amounts.

(2) **Within-option:** subjects looked at a different attribute within the same option as their next fixation.

(3) **Transitional:** subjects looked at a different attribute in a different option as their next fixation.

See Figure 2 for an example of the eye fixation transitions. We modeled our transitions from an eye-tracking study by Arieli, Ben- Ami and Rubinstein (2009), in which they denote horizontal eye movement as one that evaluates one attribute at a time and denotes a vertical movement as one that evaluates one option at a time. Our analyses mainly focus on these two types of eye movements.

*Proportion of refixations.* We calculated the proportion of fixations considered refixations to an option. A refixation is looking back at an option that has already been fully evaluated, after having already looked away at another option.

*Spatial location.* We summed the total number of fixations for each spatial position. For each trial type, we tested whether there were more fixations towards the center options of the display versus options towards the outside.

*Dynamics over trial.* We also investigated how fixation patterns changed as a trial progressed. Each trial was divided into tenths based on total number of fixations for that trial. For each decile, we calculated the proportion of fixations on each attribute, and also calculated proportions of each fixation transition. We then calculated subject specific linear coefficients for the proportions of each attribute and each eye fixation transitions and then tested whether each set of coefficients differ from zero.

### **Combined behavioral and eye-tracking analysis**

*Choice as a function of when an option is fully evaluated.* We ordered options by the sequence in which they were first fully evaluated. We then calculated for each position in the order the percentage of times the option at that position in the order was ultimately chosen.

*Choice as a function of amount within fully evaluated options.* For each trial, we ranked from largest to smallest the amounts of only those options that were fully evaluated. We then calculated for each rank in the sequence the percentage of times the option at that rank was ultimately chosen.

## **Results**

### **People simplify by not fully evaluating all options as the number of options increases**

Basic response time and eye-tracking measures suggest that subjects in both timing conditions do not employ a fully compensatory strategy. If subjects employ a fully compensatory strategy, continuing to evaluate every option to the same degree as the number of options increases, we would expect to see a linear increase in response times with the

number of options. In contrast to this, but consistent with previous work, response times largely follow Hick's Law (Hick, 1952), increasing linearly with the logarithm of the number of options. Without time pressure, as the number of options increases, there is a significant increase in response times ( $\beta = .82, p < .001$ ). See Figure 3a. Similarly, when there is time pressure, the average response times across subjects also increase linearly with the log of the number of options ( $\beta = .96, p < .001$ ). See Figure 3b. Without time pressure, there is also evidence for a small but significant nonlinear quadratic trend ( $\beta = .20, p < .01$ ), a departure from Hick's Law. There was no evidence for nonlinearity with time pressure ( $p = .80$ ).

The overall number of fixations followed the same pattern as response times. The mean number of fixations under both timing conditions increases linearly to the log of the number of options (without time pressure:  $\beta = .83, p < .001$ ; with time pressure:  $\beta = .96, p < .001$ ). See Figures 3c and 3d. Again, without time pressure, the increase in fixations is nonlinear with a slight curvature, ( $\beta = .18, p < .001$ ), but with time pressure, there is not significant nonlinearity ( $p = .08$ ).

Since response times and number of fixations do not increase in proportion to the number of options, the evaluation time per option must decrease as the number of options increases. We next test whether this led participants to skip evaluating some of the options within the choice set. We define an option as fully evaluated if the participant looked at both attributes of the option (i.e., looked at both amount and probability within an option). With and without time pressure, participants fully evaluated a smaller percentage of the total options as the number of options increased (without time pressure:  $\beta = -.90, p < .001$ ; with time pressure:  $\beta = -.93, p < .001$ ). See Figures 3e and 3f. Finally, though these metrics are affected in the same way by the number of options regardless of time pressure, subjects under

time pressure respond faster, make fewer fixations, and evaluate a smaller percentage of total options for all trial types ( $ps < .0001$ ). The next three sections test what effect not fully evaluating every option has on what people choose and what factors determine whether an option is fully evaluated or not.

### **People are less successful at maximizing and slightly more risk averse as the number of options increases**

The previous analyses suggest that participants use a simplifying strategy in response to an increasing number of options, rather than fully evaluating every option in the choice set in a compensatory manner. The next set of analyses investigates whether this simplification affects choice. The choice sets were designed so that one option, the “pop-out”, had a higher expected utility than all of the other options within the choice set. In both timing conditions, participants miss more pop-outs as the number of options increases (without time pressure:  $\beta = -.87, p < .001$ ; with time pressure:  $\beta = -.93, p < .001$ ). During 16-option trials, subjects under time pressure choose the pop-out fewer times compared to those without time pressure ( $p < .01$ ). There is no significant difference between timing conditions in other trial types. See Figures 4a and 4b. Though fewer pop-outs are chosen as the number of options increases, subjects select the pop-out at above chance levels in all conditions ( $ps < .001$ ).

The pop-out option was defined *a priori* by the experimenter, and therefore may not actually be the most subjectively valuable option to a given subject. This is especially true of subjects who are either highly risk-averse or highly risk-seeking. Therefore, one possibility is that subjects “miss” more pop-outs as the number of options increases because their degree of risk aversion is changing. We fit an expected utility model to subjects’ choices separately

for each condition (i.e., 2-option, 4-option, 8-option and 16-option) to see whether there are changes in risk aversion as the number of options increases. In both timing conditions, subjects become slightly more risk averse as the number of options increases (without time pressure:  $\beta = -.10, p < .05$ ; with time pressure:  $\beta = -.16, p < .05$ ). See Figures 4c and 4d. Risk aversion levels do not significantly differ between timing conditions.

We then determined the option with the highest subjective value for each subject, given his or her own risk preferences for each of the trial types. When taking into consideration risk preferences, subjects choose the option with the highest subjective value less often as the number of options increases (without time pressure:  $\beta = -.82, p < .001$ ; with time pressure:  $\beta = -.86, p < .001$ ). See Figure 4e and 4f. During 8-option and 16-option trials, subjects under time pressure choose the option with the highest subjective value less often than subjects without time pressure ( $p < .05$ ). Thus, even though risk aversion increases slightly as the number of options increases, this does not account for the increase in the number of pop-out options missed. Subjects are less likely to select the most valuable option as the size of the choice set increases.

### **People are not following a lexicographic non-compensatory strategy**

The previous analyses suggest that participants only fully evaluate a subset of the choice options as the size of the choice set increases, and that this leads their choices to be less consistent with utility maximization. The next set of analyses aims to identify what determines whether an option is fully evaluated and whether subjects are switching to a non-compensatory strategy. We first test whether subjects are switching to a simple lexicographic strategy as the number of options increases. In our task, two such lexicographic strategies are

possible: selecting the option with the highest probability to win or the highest payoff. If subjects are using a lexicographic non-compensatory strategy, this could explain a decrease in the number of options fully evaluated because for most options only the relevant attribute is considered.

There are several pieces of evidence against the hypothesis that subjects switch to strictly using a lexicographic strategy. First, as shown above, subjects' degree of risk aversion does not shift to extreme levels of risk seeking or risk aversion as would be expected if they were solely choosing the highest probability or highest payoff options. This is also evident in a direct test of people's choices. We find that under both timing conditions subjects choose the option with the highest probability *fewer* times as the number of options increases (without time pressure:  $\beta = -.44, p < .0001$ ; with time pressure:  $\beta = -.52, p < .0001$ ), and they also choose the option with the highest payoff *fewer* times as the number of options increases (without time pressure:  $\beta = -.78, p < .0001$ ; with time pressure:  $\beta = -.69, p < .0001$ ). See Figures 5a-5d. Subjects do choose the highest probability option at greater than chance levels, however. Without time pressure, subjects choose the highest probability option at above chance levels for 8- and 16-option trials ( $ps < .01$ ), and under time pressure, subjects choose the highest probability at above chance levels for 2-, 8-, and 16-option trials ( $ps < .05$ ). In contrast, without time pressure, subjects choose the highest payoff option at *below* chance levels for 4- and 8-option trials, and under time pressure, subjects choose the highest payoff at below chance levels for 2-, 4-, and 8-option trials. Finally, subjects' eye movements are not consistent with the use of an attribute-based heuristic. While there is a reliable increase in proportion of fixations on probability as the number of options increases,

the absolute size of this increase is small (without time pressure:  $\beta = .18, p < .05$ ; with time pressure:  $\beta = .10, p < .05$ ). See Figures 5e and 5f.

We also considered two other, more specific, heuristics: 1) priority heuristic (Brandstatter, Gigerenzer, and Hertwig, 2006) and 2) minimax regret (Savage, 1951). In our task, the priority heuristic reduces to choosing the option with highest payoff, and is therefore ruled out above. Minimax regret does make unique predictions in our task; however, subjects in both timing conditions choose the minimax regret option fewer times as the number of options increases (without time pressure:  $\beta = -.81, p < .0001$ ; with time pressure:  $\beta = -.79, p < .001$ ) and choose this option above chance for 2- and 8-option trials only (without time pressure:  $ps < .01$ ; time pressure:  $ps < .05$ ).

In sum, participants in both timing conditions choose the option with the highest probability more often than chance but less often in absolute terms as the number of options increases. They look more at probability and are more risk averse as the number of options increases, but not to an extent that would suggest an exclusive reliance on probability. Although these facts are not consistent with strict use of a simple probability-based heuristic, the increasing weight on probability needs to be explained by any proposed simplifying strategy.

### **People are not satisficing**

We then tested whether subjects employed a different non-compensatory strategy, a satisficing strategy, as the decision increased in difficulty. Satisficing involves evaluating options until reaching one that surpasses an acceptability threshold and then choosing that option (Schwartz et al., 2002). We performed two tests to determine if subjects are

employing a satisficing strategy. First, if subjects are fully evaluating options only until they find one that is acceptable, we expect to see few, if any, *refixations* of an option. Contrary to a satisficing strategy, in both timing conditions and under all trial types, about half of fixations in a trial were refixations (mean percentage of refixations = .43 to .73). Second, if participants select the first option they find that is acceptable, we expect the majority of selections to correspond to the *last option* that was fully evaluated. To test this, we ordered the items by the sequence in which they were fully evaluated (i.e., a fixation had been made to both attributes of the item), from the last item that was fully evaluated to the first, and calculated the fraction of options at each position in the sequence that were ultimately chosen. We compared this to a null distribution representing choosing randomly without an effect of order of evaluation. Inconsistent with a satisficing strategy, subjects are not more likely to choose the last option that was fully evaluated, and order of evaluation did not have a significant effect on choice. Subjects usually did not choose the last option that was fully evaluated at a level that differed from chance, and when they did, they actually chose this option at significantly below chance levels (without time pressure 4- and 8-options:  $ps < .05$ ; all others:  $ps = ns$ ). See Figures 6a-6f.

### **People simplify the choice set based on attribute values and spatial location**

If people are not adopting a simple non-compensatory lexicographic strategy or satisficing strategy as the choice set size increases, what criterion explains which options are fully evaluated and which are not? We next test two different strategies that subjects might use for reducing the number of options that need to be fully evaluated: spatial and attribute-based. With a spatial reduction strategy, subjects further evaluate a subset of options based



on their spatial locations. Finally, an attribute-based reduction strategy involves further evaluating only those options where one attribute passes a set threshold.

We next tested whether spatial location influences the options that are fully evaluated. Figures 7a-7f show the distribution of options fully evaluated in each condition, by location, in a gray-scale “heat map”. Subjects tend to fully evaluate options in the center of the screen compared to options on the outside, in both timing conditions and in all set sizes ( $p < .0001$ ). Additionally, subjects in both timing conditions also choose options in the center more often than the outside ( $ps < .0001$ ). Thus, spatial location does play a role in determining what options subjects fully evaluate.

We then examined whether the amount and probability of each option influence whether or not that option is fully evaluated. Without time pressure, both the amount and probability of the option predict whether the option is fully evaluated, but probability ( $\beta = .85, p < .0001$ ) is a stronger predictor than amount ( $\beta = .58, p < .0001$ ). The same pattern emerges when under time pressure, where probability ( $\beta = .73, p < .0001$ ) is a stronger predictor than amount ( $\beta = .40, p < .0001$ ). See Figure 8a-8d for partial regression plots to see how each attribute uniquely affects the number of subjects who fully evaluated a particular option. These data suggest that participants also use an attribute-based strategy, fully evaluating those options where one attribute is high.

### **Dynamics over time: People initially scan probabilities**

The previous analyses demonstrate that people simplify the choice set based on attribute levels, and especially probability. That is, options with low probability are less likely to be fully evaluated, whereas options with high probability are more likely to be fully

evaluated. We now test whether subjects use an EBA strategy or whether subjects use a combination strategy that involves reducing based on an attribute, initially like an EBA strategy, but then switching to a compensatory strategy to make a decision. In order to test these strategies, we explore the dynamics of this simplification process by examining how eye fixations and fixation transitions change across the course of a trial.

First, we examine how the proportion of fixations on probability versus amount changes as a trial progresses. Across all trial types in both timing conditions, subjects initially have a greater proportion of fixations on probability, and the proportion of fixations on probability decreases as the trial progresses (without time pressure:  $p_s < .05$ , median  $\beta_s = -.007$  to  $-.013$ ; time pressure:  $p_s < .05$ , median  $\beta_s = -.008$  to  $-.018$ ). See Figures 9a-9h.

Next, we analyze how eye fixation sequences change throughout a trial. We categorize fixation transitions based on whether the current fixation is on either probability or amount and whether the next fixation will be on 1) the same attribute but in a different option (attribute-based eye movements) or 2) a different attribute within the same option (option-based eye movements). Without time pressure, during 4-, 8-, and 16-option trials, subjects employ fewer attribute-based eye movements across probabilities as a trial progresses (median  $\beta_s = -.013$  to  $-.018$ ,  $p_s < .0001$ ). Similarly, with time pressure, the employment of attribute-based eye movements across probabilities decreases throughout a trial (all trials: median  $\beta_s = -.009$  to  $-.022$ ,  $p_s < .01$ ). Thus, in both timing conditions, subjects are more likely to fixate probabilities, and more likely to scan between probabilities in different options, early in the trial.

**Dynamics over time: People then fully evaluate a subset of options (without time pressure) or scan amounts (with time pressure)**

Other aspects of the fixation transitions differ depending on whether subjects are under time pressure or not. Subjects without time pressure switch to a compensatory strategy and employ a greater number of alternative-based eye movements as a trial progresses during 8- and 16-option trials (median  $\beta$ s = .004 and .002,  $ps < .05$ ), while subjects under time pressure do not show this pattern. In contrast, for all trial types, subjects under time pressure continue to use a non-compensatory strategy and employ a greater number of attribute-based eye movements *across amounts* as a trial progresses (median  $\beta$ s = .007 to .017,  $ps < .01$ ). Subjects without time pressure also employ this attribute-based pattern, but only for 2- and 4-option trials (median  $\beta$ s = .01 & .007,  $ps < .05$ ). See Figures 10a-10h. Thus, subjects without time pressure tend to increasingly rely on alternative-based eye movements as the trial progresses, switching from scanning probabilities to evaluating alternatives. In contrast, subjects under time pressure tend to increasingly scan across amounts as the trial progresses, switching from scanning probabilities to scanning amounts.

Do subject's choices reflect these eye fixation movement dynamics? To answer this question, we look at which option, of the options fully evaluated, subjects choose for 4-, 8-, and 16-option trials. Subjects without time pressure do not choose the option with the highest amount (amongst those options that are fully evaluated) most often. Instead, subjects are most likely to choose the third highest amount. In contrast, subjects under time pressure choose the option with the highest amount (amongst those options that are fully evaluated) the most. See Figures 11a-11f. Consistent with eye-tracking data, subjects' choices suggests that subjects without time pressure tend to employ a combination non-compensatory and

compensatory strategy by reducing the choice set based on the attributes and then tend to choose in a compensatory manner amongst the options that are fully evaluated. In contrast, subjects under time pressure are more likely to use a non-compensatory EBA strategy, especially as the number of options increases, by first reducing the choice set based on probabilities and then select the remaining option with the highest payoff.

## **Discussion**

In this present investigation, we sought to identify the type of simplifying strategies people employ in the face of increased decision difficulty and systematically examine the computational complexity-accuracy tradeoff in decision strategy selection. Consistent with our hypothesis, for both timing conditions, subjects do not employ a fully compensatory strategy. Instead, in both timing conditions, subjects simplify by fully evaluating a smaller percentage of options as the number of options increases, where fully evaluating involves fixating on both amounts and probabilities of the option. Additionally, in both conditions, subjects are more likely to fully evaluate options with higher probabilities suggesting subjects reduce the option sets based on probabilities.

However, subjects in the different timing conditions diverge in how they make their decisions after reducing the choice set. Subjects without time pressure tend to use a combination strategy where they fully evaluate the remaining subset of options, as evidenced by greater employment of alternative-based eye-movements. In contrast, subjects under time pressure and facing more extreme levels of difficulty tend to continue to use a non-compensatory strategy by scanning across the amounts of the remaining subset of options. Furthermore, these same subjects are then more likely to select the remaining option with the

highest payoff, which is not the case for subjects without time pressure. Thus, subjects without time pressure tend to employ a compensatory strategy to make a decision after reducing the option set while subjects under time pressure tend towards a similar but simpler strategy, elimination-by-aspects, and continue to focus on a single attribute at a time to make a decision. These results are consistent with our hypothesis and the adaptive decision maker framework, where strategy selection in response to incremental increases in difficulty changes in a gradual rather than categorical manner. More specifically, subjects tend to use a mixed compensatory and non-compensatory strategy in response to increases in the number of options, but then shift a simpler non-compensatory strategy when the decision increases even more with time pressure.

Surprisingly, previous research does not completely capture our findings, and the half dozen strategies previously noted do not appear to fully explain the simplifying strategies employed during our task. In our investigation, we do not find evidence for switching to a simplistic heuristic or satisficing strategy as difficulty increases. Although subjects appear to show a stronger preference for probabilities as the number of options increases, the increase is slight and much less than what we would expect to see if a subject bases their decisions primarily on one attribute. Contradictory to a satisficing strategy, subjects tend not to choose the last option that was fully evaluated, and order of evaluation does not have a significant effect on choice. However, we find evidence that subjects reduce the number of options for further evaluation. In addition, both spatial location and attribute levels influence which options are fully evaluated, suggesting that reduction is not random.

Our study finds evidence that a person's response to increasing difficulty is adaptive in two ways. First, our subjects adapt to difficulty by using the available information. This

study does not have a simple or default option available for subjects to choose when facing increasing difficulty. Instead, subjects adapt to increasing difficulty by relying on attribute levels and spatial information to simplify the decision. Second, we find that subjects adapt to increasing difficulty by gradually changing their strategy as opposed to more categorical shifts in strategies. In other words, both groups of subjects employ simplifying strategies, but the group experiencing time pressure adapted to the increase in difficulty by employing a simpler strategy that requires less cognitive effort. This finding is consistent with the adaptive decision maker framework where individuals can shift across strategies at various gradations along the accuracy-effort tradeoff.

We find that, although subjects do use both probability and amount information in reducing the choice set, they rely more heavily on probability. This reliance on probability is likely adaptive given that subjects are risk-averse, and therefore weight probabilities slightly more than amounts. We would predict, then, that subjects would focus on the most heavily weighted attribute first in other kinds multi-attribute decisions. In our study, we find that subjects' decisions are ultimately made using both attributes, whether with an attribute-based reduction or elimination-by-aspects strategy. Again, we think this is likely adaptive, since subjects place weight on both probabilities and amounts. In other kinds of multi-attribute decisions, though, attribute weights may be less balanced and subjects might collapse to attribute-based heuristic more readily. Future research should test how strategy selection depends on initial preferences in a more detailed fashion.

Our evidence for the adaptive decision maker framework hinges on extracting more detailed information from eye-tracking measures. One of our critical eye-tracking measures is whether an option is “fully evaluated”, which involves evaluating fixations to multiple

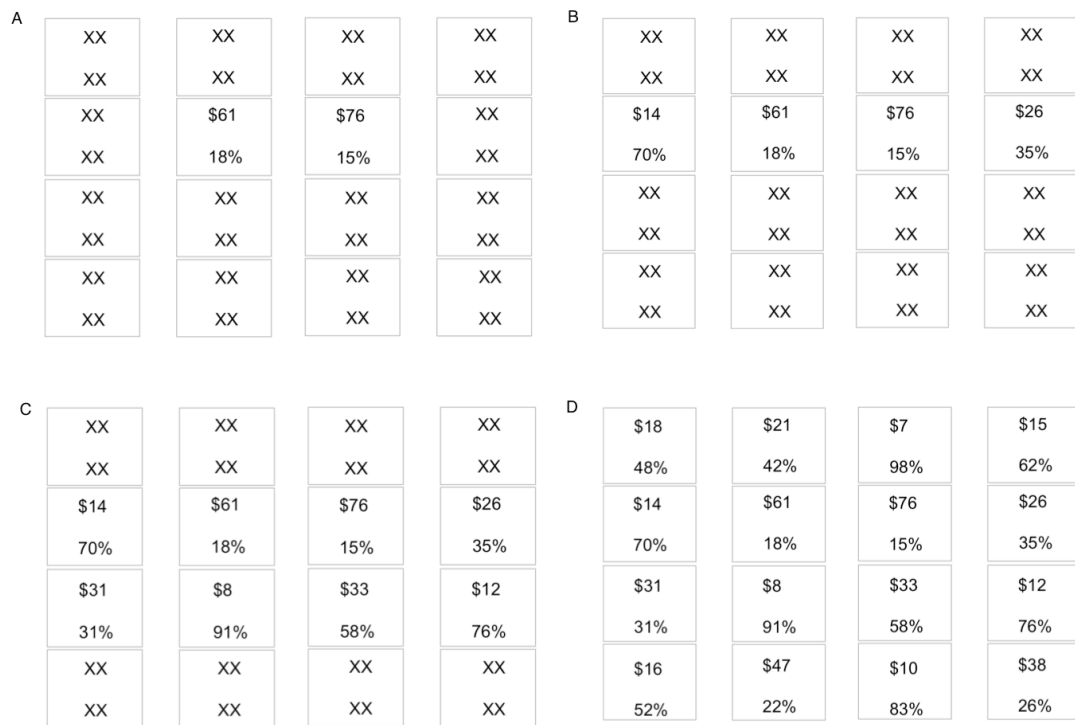
ROIs jointly. We also combine behavioral and eye-tracking measures to create richer metrics that allow us to examine specific aspects of decision-making strategies. By combining eye-tracking and choice measures, we are also able to rule out satisficing as a strategy. By combining eye-tracking and choice measures and by examining eye fixation patterns over time, we are able to distinguish elimination-by-aspects from an attribute-reduction strategy. Our results provide proof of principle that more quantitative tests of the computational complexity-accuracy tradeoff hypothesis are both possible with eye-tracking measures and merited given our results. This framework can provide rich predictions in a variety of different choice domains and for a variety different effort manipulations, and our results hold promise that such detailed predictions could be testable with eye-tracking techniques.

Future research also needs to examine how well our findings generalize to less well-controlled settings. The laboratory environment allows us to isolate and control all variables of interest and make very precise eye movement measurements, but a laboratory setting may not be representative of the kinds of environments in which people typically make decisions. If our analysis techniques can be paired with advances in mobile eye-tracking technology (Boening et al., 2006; Bulling and Gellersen, 2010), future studies could investigate how well our findings generalize to a wider variety of decision-making settings. For instance, future studies could examine decisions that involve many options in stores, restaurants, car dealerships, or other business settings.

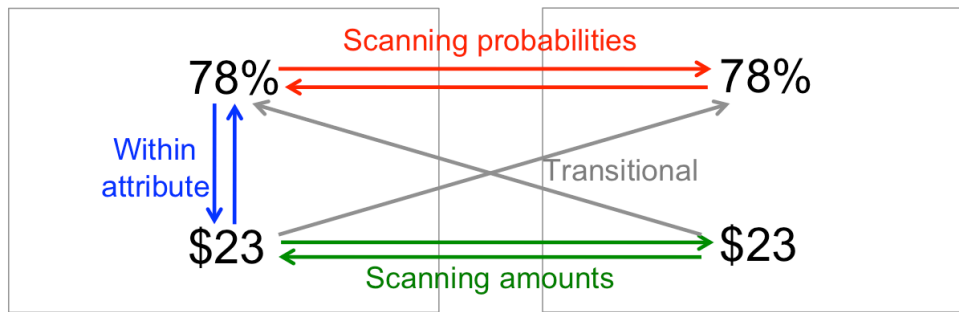
The current study suggests that when presented with many options, people initially reduce the number of options based on probability. Subjects without time pressure then tend to employ a compensatory strategy by fully evaluating the remaining options, while those under time pressure and facing more difficulty tend to employ a similar but simpler attribute-

based strategy, elimination-by-aspects. Our methods for analyzing eye-tracking data move beyond previous studies and make it possible to identify and distinguish the subtleties in decision strategies. Additionally, by varying the difficulty of the task more incrementally and collecting finer-grained process measures, we are able to detect that subjects simplify in a more gradual manner and that decision strategy selection may be more graded and less categorical than often portrayed. Previous studies have proposed many different strategies in response to increasing number of options and increasing difficulty. Our findings provide empirical support that strategy selection is based on an effort-accuracy framework, where different strategies reflect different points on the computational complexity-accuracy tradeoff as originally proposed by the Adaptive Decision Maker.

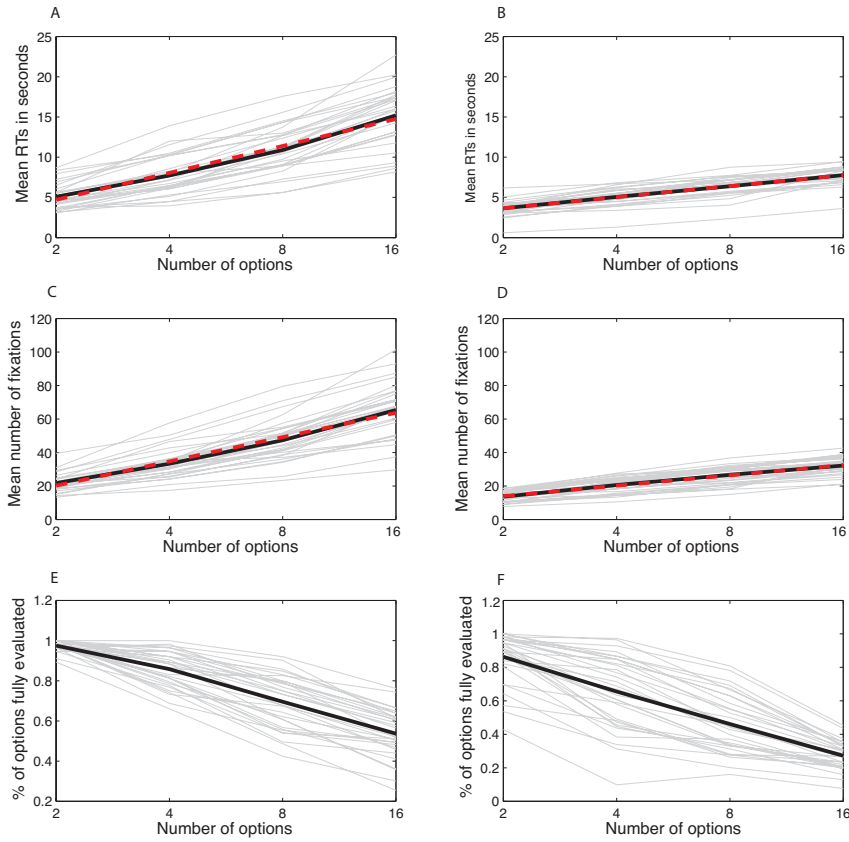




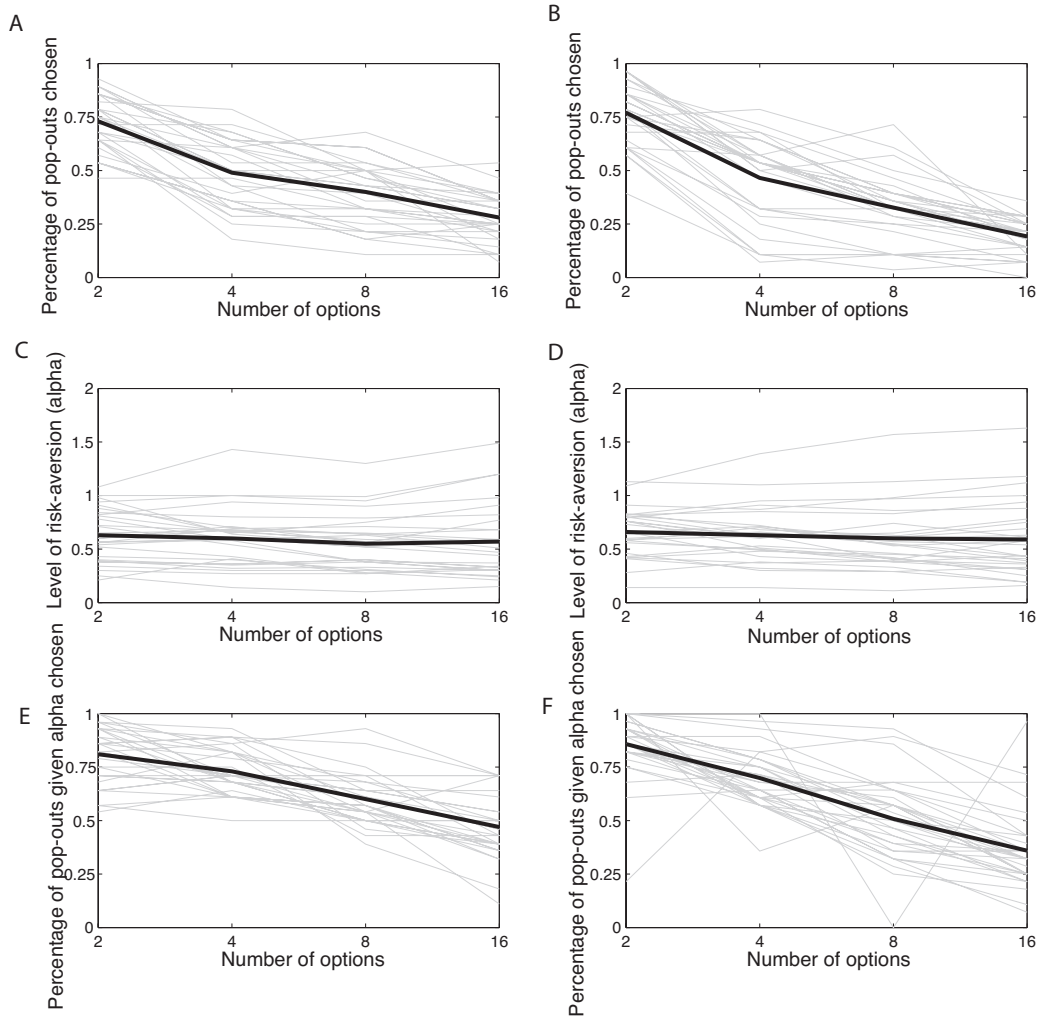
**Figure 1.** Example of each trial type. **(A)** 2-option trial **(B)** 4-option trial **(C)** 8-option trial **(D)** 16-option trial



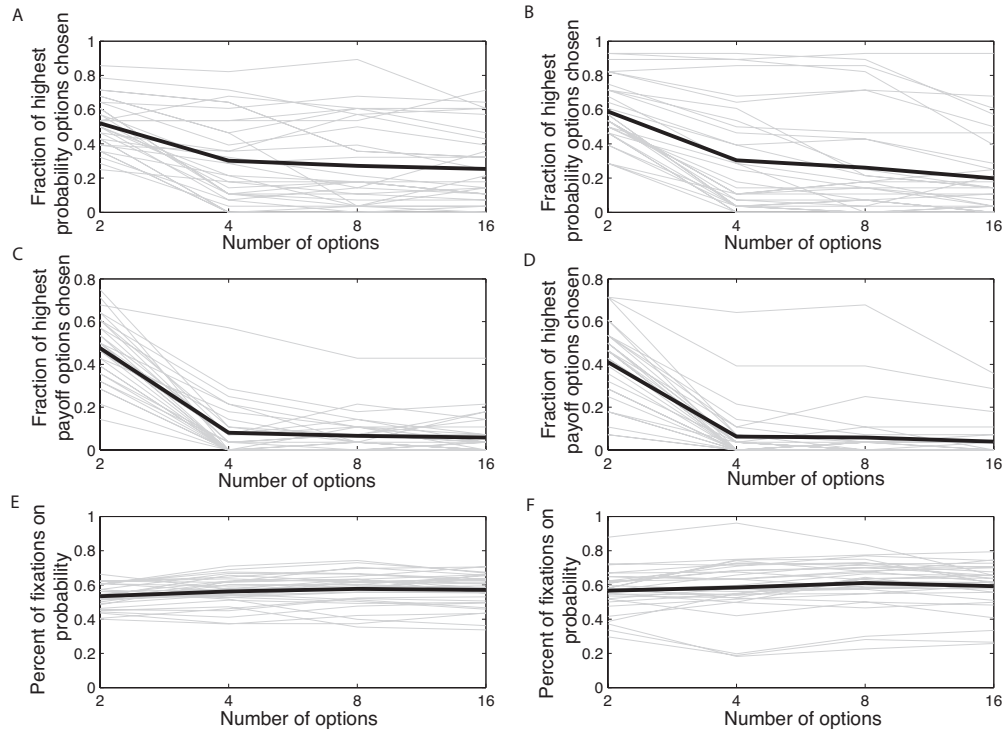
**Figure 2.** Illustration of fixation transitions. The blue lines denote within-option fixation transitions where subjects looked at a different attribute within the same option as the next fixation. The red and green lines denote within-attribute fixation transitions, where red lines denotes scanning over probabilities and green lines denotes scanning amounts. Gray lines are considered transitional fixation transitions where subjects looked at a different attribute in a different option as their next fixation.



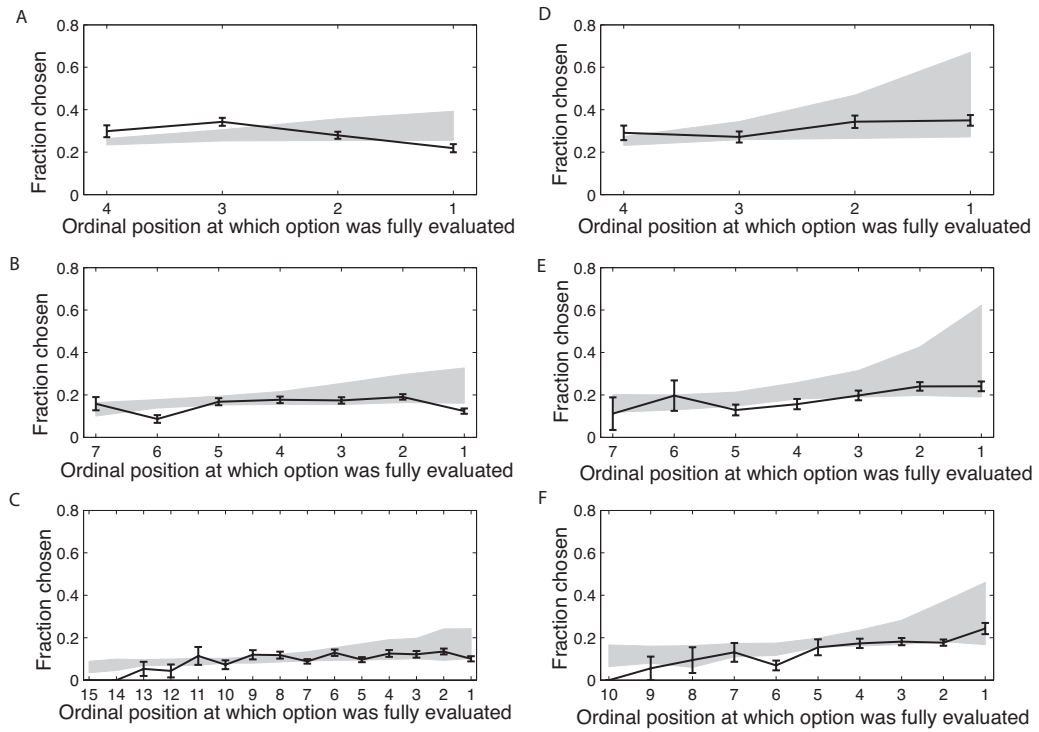
**Figure 3.** Response times, number of fixations and percentage of options fully evaluated. Light gray lines represent each individual subject. Bolded black lines represent the means across subjects. The dashed red lines illustrate Hick's Law (Hick, 1952) as a comparison (increasing linearly with the logarithm of the number of options). First column of figures are without time pressure. Second column of figures are with time pressure. **(A)** Mean response times for each option type *without* time pressure. **(B)** Mean response times for each option type *with* time pressure. **(C)** Mean number of fixations for each option type *without* time pressure. **(D)** Mean number of fixations for each option type *with* time pressure. **(E)** Percentage of total options fully evaluated for each option type *without* time pressure. **(F)** Percentage of total options fully evaluated for each option type *with* time pressure.



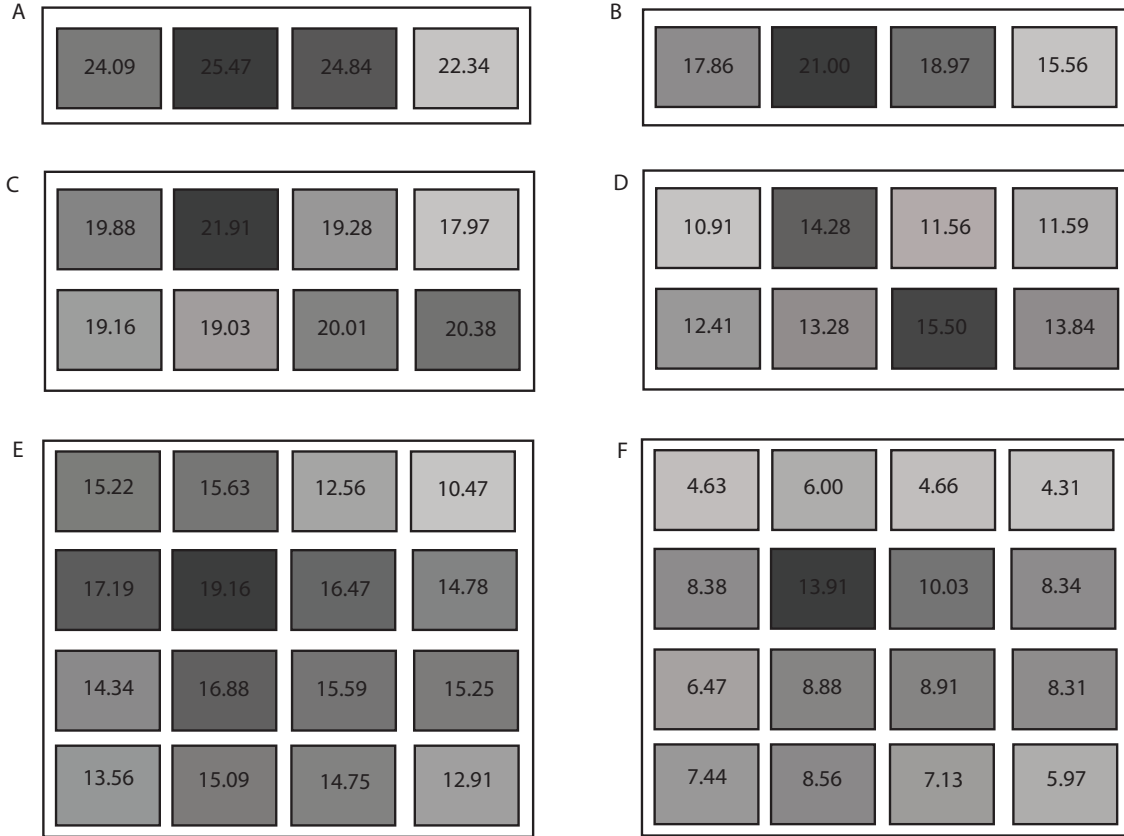
**Figure 4.** Simplification affects choice. Light gray lines represent each individual subject. Bolded black lines represent the means across subjects. First column of figures are without time pressure. Second column of figures are with time pressure. **(A)** Percentage of pop-outs chosen for each option type *without* time pressure. **(B)** Percentage of pop-outs chosen for each option type *with* time pressure. **(C)** Level of risk-aversion (alpha value) for each option type *without* time pressure. **(D)** Level of risk-aversion for each option type *with* time pressure. **(E)** Percentage of pop-outs (tailored to each subject's alpha value) chosen for each option type *without* time pressure. **(F)** Percentage of pop-outs (tailored to each subject's alpha value) chosen for each option type *with* time pressure.



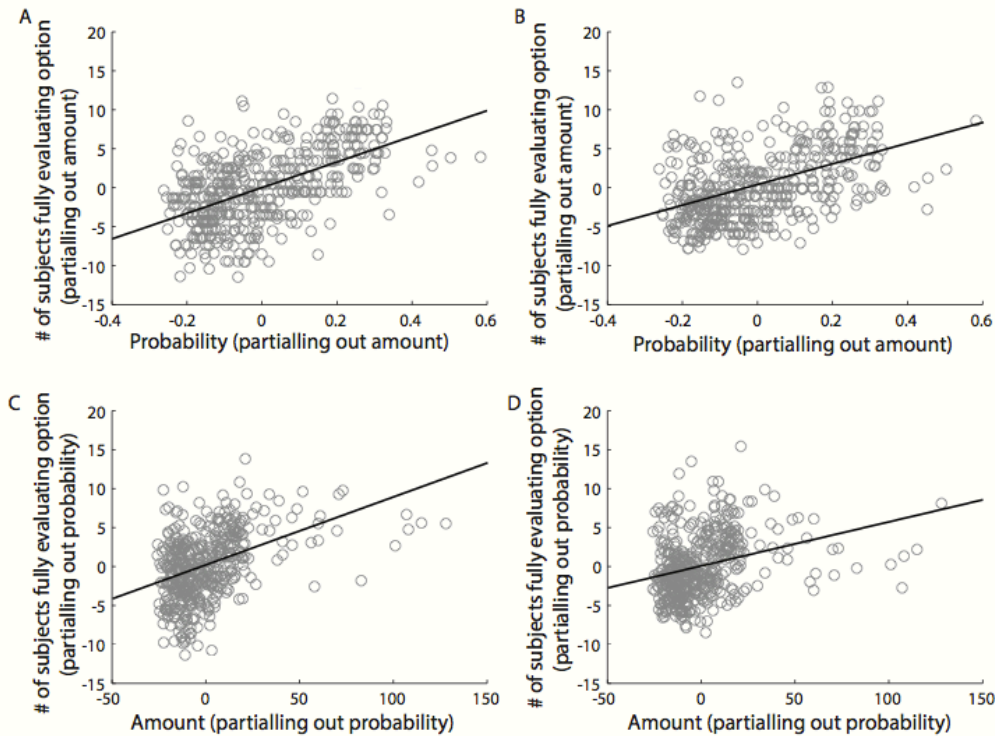
**Figure 5.** Subjects do not maximize on one attribute. Light gray lines represent each individual subject. Bolded black lines represent the means across subjects. First column of figures are without time pressure. Second column of figures are with time pressure. **(A)** Percentage of highest probability options chosen for each option type *without* time pressure. **(B)** Percentage of highest probability options chosen for each option type *with* time pressure. **(C)** Percentage of highest payoff options chosen for each option type *without* time pressure. **(D)** Percentage of highest payoff options chosen for each option type *with* time pressure. **(E)** Percentage of total fixations on probability for each option type *without* time pressure. **(F)** Percentage of total fixations on probability for each option type *with* time pressure.



**Figure 6.** Subjects do not choose the last option that was fully evaluated. Gray shaded area represents choosing randomly without an effect of order of evaluation. First column of figures are without time pressure. Second column of figures are with time pressure. **(A)** Fraction of options chosen at each ordinal position at which option was fully evaluated during 4-option trials *without* time pressure. **(B)** Fraction of options chosen at each ordinal position at which option was fully evaluated during 4-option trials *with* time pressure. **(C)** Fraction of options chosen at each ordinal position at which option was fully evaluated during 8-option trials *without* time pressure. **(D)** Fraction of options chosen at each ordinal position at which option was fully evaluated during 8-option trials *with* time pressure. **(E)** Fraction of options chosen at each ordinal position at which option was fully evaluated during 16-option trials *without* time pressure. **(F)** Fraction of options chosen at each ordinal position at which option was fully evaluated during 16-option trials *with* time pressure.

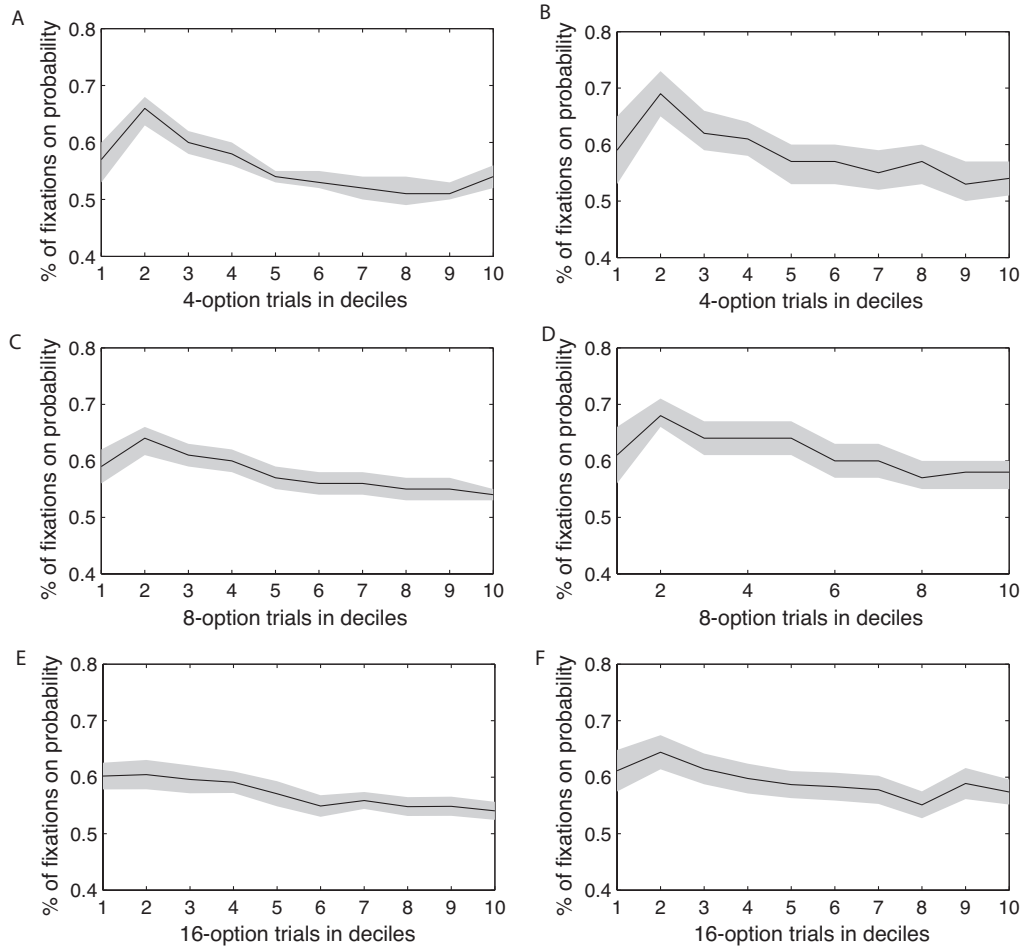


**Figure 7.** Distribution of options fully evaluated by location. Darker gray means that option location was more likely to be fully evaluated. First column of figures are without time pressure. Second column of figures are with time pressure. **(A)** Average number of trials where option, by location, was fully evaluated for 4-option trial *without* time pressure. **(B)** Average number of trials where option, by location, was fully evaluated for 4-option trial *with* time pressure. **(C)** Average number of trials where option, by location, was fully evaluated for 8-option trial *without* time pressure. **(D)** Average number of trials where option, by location, was fully evaluated for 8-option trial *with* time pressure. **(E)** Average number of trials where option, by location, was fully evaluated for 16-option trial *without* time pressure. **(F)** Average number of trials where option, by location, was fully evaluated for 16-option trial *with* time pressure.

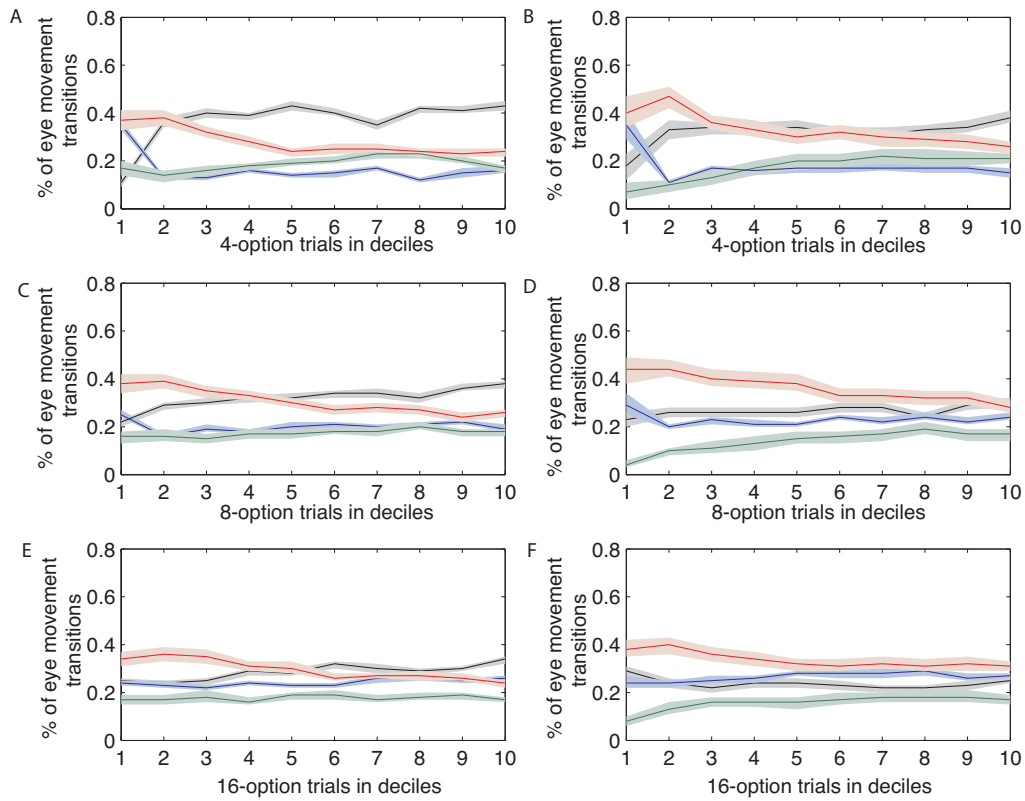


**Figure 8.** Partial correlation plots to see unique effects of each attribute **(A)** Options with higher probability are more likely to be fully evaluated after controlling for amount of the options (*without* time pressure). **(B)** Options with higher probability are more likely to be fully evaluated after controlling for amount of the options (*with* time pressure). **(C)** Options with higher amounts are more likely to be fully evaluated after controlling for probability of the options but to a lesser degree (*without* time pressure). **(D)** Options with higher amounts are more likely to be fully evaluated after controlling for probability of the options but to a lesser degree (*with* time pressure).

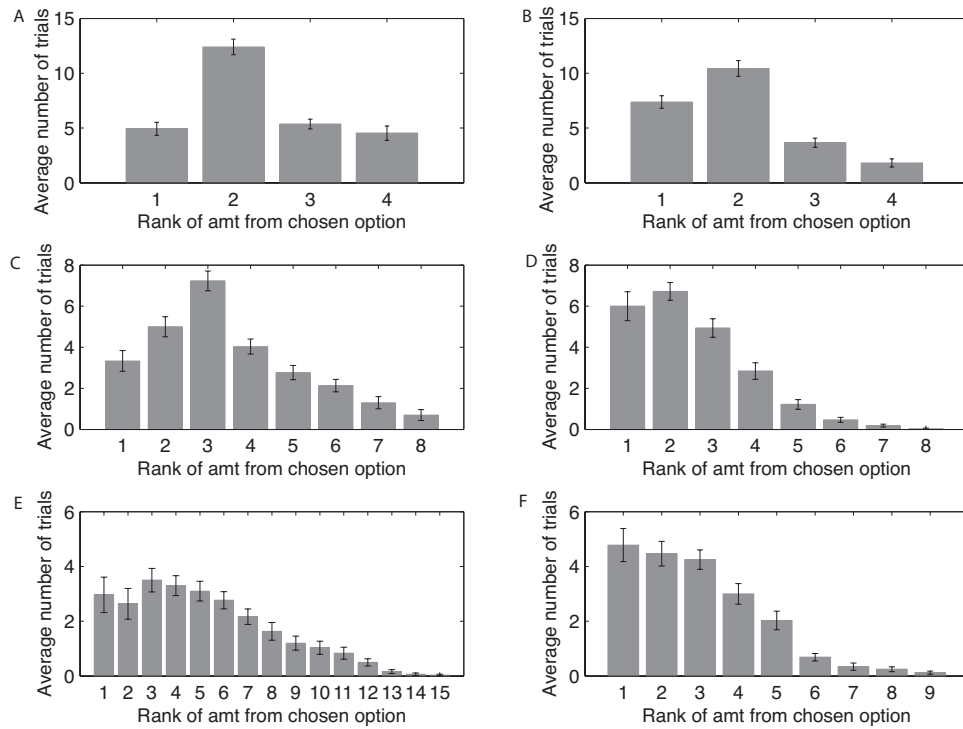




**Figure 9.** Percentage of fixations on probabilities. Trials are split into deciles. Black line represents the mean. The shaded gray surrounding the mean represent SEMs. First column of results are without time pressure. Second column of results are with time pressure. **(A)** Percentage of totally fixations on probability as a trial progresses during 4-option trials *without* time pressure. **(B)** Percentage of totally fixations on probability as a trial progresses during 4-option trials *with* time pressure. **(C)** Percentage of totally fixations on probability as a trial progresses during 8-option trials *without* time pressure. **(D)** Percentage of totally fixations on probability as a trial progresses during 8-option trials *with* time pressure. **(E)** Percentage of totally fixations on probability as a trial progresses during 16-option trials *without* time pressure. **(F)** Percentage of totally fixations on probability as a trial progresses during 16-option trials *with* time pressure.



**Figure 10.** Fixation transitions change as trial progresses. Trials are split into deciles. Red lines: attribute-based fixation transitions over probabilities; Green lines: attribute-based fixation transitions over amounts; Blue lines: option-based fixation transitions; Gray lines: transitional eye fixation transitions. The shaded colors surrounding each mean represent SEMs. The first column of results represent without time pressure. The second column of results represent with time pressure. **(A)** Percentage of each fixation transition as a trial progresses during 4-option trials *without* time pressure. **(B)** Percentage of each fixation transition as a trial progresses during 4-option trials *with* time pressure. **(C)** Percentage of each fixation transition as a trial progresses during 8-option trials *without* time pressure. **(D)** Percentage of each fixation transition as a trial progresses during 8-option trials *with* time pressure. **(E)** Percentage of each fixation transition as a trial progresses during 16-option trials *without* time pressure. **(F)** Percentage of each fixation transition as a trial progresses during 16-option trials *with* time pressure.



**Figure 11.** Selected option from fully evaluated options. Error bars represent SEMs. First column of results represent without time pressure. Second column of results represent with time pressure. **(A)** Average percentage of times the option at each rank was chosen from among amounts from options that were fully evaluated during 4-option trials *without* time pressure. **(B)** Average percentage of times the option at each rank was chosen from among amounts from options that were fully evaluated during 4-option trials *with* time pressure. **(C)** Average percentage of times the option at each rank was chosen from among amounts from options that were fully evaluated during 8-option trials *without* time pressure. **(D)** Average percentage of times the option at each rank was chosen from among amounts from options that were fully evaluated during 8-option trials *with* time pressure. **(E)** Average percentage of times the option at each rank was chosen from among amounts from options that were fully evaluated during 16-option trials *without* time pressure. **(F)** Average percentage of times the option at each rank was chosen from among amounts from options that were fully evaluated during 16-option trials *with* time pressure.

## CHAPTER 4 – Evidence for distinct neural representations in frontal and parietal cortices for different sources of decision difficulty.

### Introduction

A remarkable feature of human cognition is the ability to adapt to the ever-changing demands of the environment. How these cognitive demands are represented in the brain has been of great interest to researchers. Previous studies have found several common brain regions in frontal and parietal cortices responding to many different forms of cognitive demand including working memory tasks (Owen, 1997; Rypma et al., 1999; Derfuss, Brass, and von Cramon, 2004), response inhibition (Barch et al., 2001; MacLeod and MacDonald, 2000; Braver, et al., 2001; Durston et al., 2002), perceptual difficulty (Grady et al., 1996; Barch et al., 1997; Koechlin, 1999), and decision difficulty (Botvinick, 2007; Ponchon et al., 2008; Shenhav et al., 2014). Additionally, meta-analytic work of functional neuroimaging studies of different cognitive demands found activation across the dorsolateral surfaces of the frontal lobe, mid-ventrolateral and anterior cingulate regions, and in and around the intraparietal sulcus (Duncan and Owen, 2000). This network of regions, coined the multiple-demand or MD system, has been found to respond to a broad range of different cognitive tasks regardless of the specific demands.

Although similar regions are implicated to be more active during demanding tasks, previous studies have typically used a single manipulation of cognitive demand making it difficult to single out a common neural network across different demands. Moreover, these studies have relied on traditional group analysis and meta-analyses of activation peaks pooled across studies, which can overestimate overlap due to neuroanatomical variability across subjects. This can result in overlapping activations across different tasks even when these

tasks activate non-overlapping brain regions in each subject (Saxe, Brett, and Kanwisher, 2006; Fedorenko et al., 2010). More recent work by Fedorenko et al. (2013) addressed these limitations by testing the engagement of the multiple demand system across different tasks. By defining regions of interest (ROIs) in individual subjects, the authors found overlapping activation on the individual subject level across the MD system for a number of different demanding tasks. To date, this is the most compelling evidence for a common domain general network for responding to cognitive demands.

Despite the evidence for overlapping fMRI activity on an individual subject level across these regions, it is not clear whether these different demanding tasks engage these frontal and parietal regions in the same way. In other words, do these regions actually have common patterns of activation across the different demanding tasks? The subject-specific ROI approach involves averaging across voxels to extract single measures of overall level of activity in a region. This method and traditional univariate group analyses test questions regarding where functions are performed or where the activation occurred, while analyses investigating the pattern of voxel activity can answer the question of how information is neurally represented or how the neural region is engaged (Haxby, 2012). Thus, even if the fMRI activity evoked by the different tasks are overlapping in specific regions, these tasks can still have distinct patterns of voxel activity. Notably, a recent study by Woo and colleagues (2014) found distinct neural patterns of activity for social and physical pain by using multivariate pattern analysis (MVPA; Haxby et al., 2001) even though these types of pains have overlapping fMRI activity (Kross et al., 2011).

Here, we build on previous studies to test the question of whether different forms of cognitive demand share common neural representation or whether these different demands

have distinct neural representation across the multiple demand system. We use decision-making to test this question because previous studies have established the many ways in which decisions can be made more demanding and complex, such as increasing the number of options, increasing time constraints, or changing the format of the decision context (see Payne, Bettman, and Johnson, 1993). Further, previous research has also demonstrated the ability of individuals to adapt to different decision demands by employing cognitive flexibility (Payne, Bettman, and Johnson, 1993).

In this investigation, we use one type of decision-making task, intertemporal choice task, and manipulate the task in four different ways to induce increases in difficulty. Each manipulation has an easier control condition that is the same across all manipulations. We chose this task design so that we only changed the actual demand that was involved, but the actual evaluative judgment remained the same. Notably, if the different conditions have distinct neural representation even though the underlying task is the same, it would provide stronger evidence against commonality. During the experiment, subjects provided their subjective ratings of how difficult they thought their decisions were, which served as a manipulation check to test whether our difficult tasks were in fact more difficult. Using both group-level and individual-level analyses, we found widespread activation in the frontal and parietal cortices of the multiple demand system, which is consistent with previous results. When we ran analyses on a voxel level and investigated the pattern of activation, we found some evidence for shared representation across the different manipulations. But, more importantly, we also found evidence for distinct patterns of activity across our different manipulations throughout the MD system, which provides evidence against the view that the multiple demand system as a general signal of demand across different tasks.

## Material and Methods

*Subjects.* Twenty-one healthy subjects with normal or corrected-to-normal vision were recruited from the University of Pennsylvania community. All subjects were compensated for their time on both testing days and received an additional monetary payment based on their decisions in the tasks on both testing days. All participants provided consent in accordance with the procedure approved by the University of Pennsylvania institutional review board. Two subjects were excluded due to technical issues with their anatomical images. This left us with 19 subjects whose functional data were analyzed (53% females; mean age = 23.2).

*Tasks.* All participants completed two sessions, separated by an average of  $7 \pm 2$  days. Both sessions involved a monetary delay discounting task, where participants made a series of decisions between a smaller amount of money available now and a larger amount of money available after a delay (e.g., \$10 now vs. \$34 in 30 days). We chose this task because neural activity in this task has been well characterized in previous studies (Kable and Glimcher, 2007; Kable and Glimcher, 2010; Senecal et al., 2012; Cooper and Kable, 2015). The first session took approximately 30 minutes, while the second session took approximately one hour. At the end of each session, one trial was randomly selected and the participant was paid via debit card according to one of their choices (Kable and Glimcher, 2007).

The first session served as a behavioral screening task in order to estimate each subject's discount rate, a measure of how much the subject devalues or discounts rewards to be received in the future. This estimate was then used to tailor the experimental task in the

second session according to each subject's discount rate. In the first session, the discounting task involved 102 choices. The range of monetary values for the immediate reward varied from \$10-\$34, and amounts for the larger reward were \$25, \$30, or \$35. Delays ranged from 1- 180 days. All subjects saw the same choices, but the choices were presented in a different random order for each subject. Subjects had 6 seconds to make a choice between two options. After a choice was made, a feedback screen was displayed for 1 second denoting a checkmark for the chosen option.

In the second session, subjects made 256 choices during an fMRI session. The monetary values for the immediate reward ranged from \$5 to \$36. The amounts for the delayed reward ranged from \$6 to \$80 and the delays ranged from 1 – 180 days. The experimental task involved four different manipulations inducing increased difficulty: (1) disfluency (words instead of numbers and varying delay units instead of consistent delay units); (2) multioption (4 options instead of 2); (3) time pressure (respond in 1.5 s instead of 6 s), (4) subjective value difference at or around 0 (choices near indifference instead of far from indifference). See Figure 1a for an example of each manipulation. Since RTs typically increase as choices become more demanding (Wilcox, 1993; Yeung and Monsell, 2003) it is often difficult to dissociate increases in demand from time on task. We included time pressure as a manipulation to dissociate time on task from demand. For all trials except for when the value difference was near indifference, the difference in subjective value between the two options in a trial ranged from \$5 to \$15. Additionally, in all but time pressure trials, subjects had 6 seconds to respond. Once a subject responded a red box outlined the chosen option for 0.5 seconds. Then, a 1.5 second blank intertrial interval (ITI) screen was presented to the subject. If subjects submitted before 6 seconds, the ITI absorbed the remaining time



making the blank ITI screen longer. For time pressure trials, the ITI was longer (6 seconds) to compensate for the shorter trial periods. If subjects submitted their response before 1.5 seconds, the ITI still absorbed the remaining time. This ensured equal number of trials across manipulations and ensured that block lengths were equal across the whole experiment. It also discouraged subjects from responding rapidly in an attempt to complete the task quickly. Each of the four manipulations was compared to an easy control task. The easy control task was the same for all four conditions, which included two options that were far apart in subjective value and presented numerically to increase fluency.

We used a block design for our fMRI experimental session, and the experimental task consisted of eight scan runs. Each scan run was divided into four hard blocks and four easy blocks, and the easy and hard blocks alternated within each scan run. Each scan run included only one manipulation of difficulty, and each difficulty manipulation was conducted in two scan runs. By having two scan runs of each manipulation, we were able to compare the pattern of neural activity for within manipulations (e.g., disfluency scan run 1 vs. disfluency scan run 2) and the pattern of activity between manipulations (e.g., disfluency scan run 1 vs. multioption scan run 1). Additionally, the order of easy and hard blocks was counterbalanced across runs, and the order of the difficult manipulations was counterbalanced across subjects. After each block, subjects were asked “How difficult did you find the last set of decisions?” Subjects moved a cursor along a line that went from “not difficult at all” to “very difficult” to submit their answers. See Figure 1b for an illustration. Each subject was told to use the same scaling across the whole experiment.

*Behavioral Data Analysis.* We estimated discount rates using optimization routines implemented in Matlab (Mathworks). Discount rates in this experiment were calculated

assuming a hyperbolic discounting model,  $SV = A/(1 + kD)$ , where SV denotes an option's estimated subjective value,  $A$  and  $D$  represent the option amount and delay, and  $k$  represents the individual's estimated discount rate (Mazur, 1987).  $K$  values across subjects ranged from .005 to .16 with the median  $k = .02$ . On average,  $92 \pm .7\%$  of choices were consistent with the estimated discount rates. The distribution of  $k$  values is consistent with other studies (e.g., Senecal et al., 2013; Cooper and Kable, 2015).

Our fMRI analyses assumed that each manipulation was more difficult than the control trials. To check for a possible violation of this assumption, we used the subjective ratings of difficulty to test whether each manipulation was considered more difficult than its respective easy control blocks. We averaged each subject's subjective ratings of difficulty for each manipulation and for each of the corresponding easy control blocks, and then compared the subjective ratings of each manipulation to its easy control.

Additionally, we compared median response times (RTs) between the hard and easy blocks for each manipulation. Response times were calculated as the duration from onset of trials to the submission of choice.

*fMRI Data Acquisition and Preprocessing.* Anatomical and functional brain images were acquired using a 3T Siemens Trio MRI scanner with a 32-channel head coil. Each session began with the acquisition of a high-resolution T1-weighted anatomical image (MPRAGE sequence; TR = 1630 ms; TE = 3.11 ms; TI = 1100ms; flip angle, 15°; 160 axial slices; voxel size, 0.9375x0.9375x1.000MM; matrix, 192x256) and a T2-weighted anatomical image (TR = 7000 ms; TE = 90.0ms; flip angle, 180°; 44 axial slices; voxel slices, 0.75x0.75x3.0mm; matrix 256x256). Functional images were collected at TR = 2.5s, TE =

30ms, 45 axial slices in interleaved order, and 3x3x3mm voxels. To reduce signal dropout in orbitofrontal cortex, we used a slice angle 30 degrees to the plane of the anterior and posterior commissures (Deichmann et al., 2003). The resulting slice prescription provided whole or near-whole brain coverage across participants.

Pre-processing and data analysis for individual subjects were performed using FMRIB Software Library (FSL; Jenkinson et al. 2012; Woolrich et al., 2009; Smith et al., 2004). Functional images were corrected for differences in slice time acquisition and then de-obliques to correct for the 30 degree tilt slice acquisition. Data were then motion corrected by spatially realigning each image with the central image in the run. Motion-corrected functional data were co-registered to the participant's anatomy and to the MNI template, which included alignment to the T2-weighted anatomical image, alignment to the high-resolution MPAGE image, and then nonlinear warping to the MNI template (Jenkinson, 2002). Non-brain matter was removed from the anatomical images prior to registration (Smith, 2002). Warped images were spatially smoothed using a Gaussian kernel of FWHM 5mm.

*Whole brain analysis.* Each participant's functional data were modeled following a block design analysis using a general linear model (GLM). The GLM tested for regions activating for the hard > easy contrast for each of the 4 manipulations. The GLM for each manipulation included two regressors: (1) block period of decisions not including the rating period (total of 4 trials + ITIs = 28 s), and (2) whether the block was our experimental hard block (denoted by 1). The subject level contrasts were then combined into a higher-level group analysis using FMRIB's Local Analysis of Mixed Effects (FLAME). FLAME uses sophisticated methods for modeling inter-subject random-effects component of the mixed-

effects variance by using MCMC (Markov Chain Monte Carlo randomization) to calculate an accurate estimation of the true random effects and degrees of freedom at each voxel. Z statistic images were thresholded at  $z > 2.3$  and cluster corrected at  $p < .05$  (Worsley, et al., 1992). We overlayed the four hard > easy contrasts maps to look for overlapping areas across the four conditions. To find unique activation for disfluency, we first combined the hard > easy contrast maps for the other three manipulations. We then subtracted the combined hard > easy contrast map from the disfluency hard > easy contrast map, which left us with a map showing regions that were only recruited for disfluency. We then did this for the other three manipulations.

*Functional Region of Interests analysis.* For the individual-subject functional ROI (fROI) analyses, we adapted the procedure set forth by Fedorenko et al. (2013). Each scan run's hard > easy contrast served as an independent localizer contrast (thresholded at  $p < .05$ , uncorrected), resulting in two different localizers for each contrast. Having two independent localizers for each manipulation allowed us to compare fMRI activity within each manipulation (e.g., disfluency activity in one scan run was estimated from an fROI defined by the disfluency manipulation from another scan run) and activity between manipulation (e.g., disfluency activity in one scan run was estimated from an fROI defined by the multioption manipulation from another scan run). We also used previously reported anatomical ROI masks of the multiple-demand system (See Figure 2; Duncan and Owen, 2000; see Fedorenko et al., 2013).

To define fROIs, we intersected each of the 9 anatomical ROIs with each of the 8 subject specific localizer contrasts. Therefore, each subject had a set of 72 fROIs created from the anatomical ROIs and his/her own activation maps. It is important to note that each

localizer used for fROI definition was independent from the data used to estimate the effects. Thus, each fROI served as an ROI for 7 of 8 scan runs. We then extracted average parameter estimates, converted to % change signal, from each individual fROI. To estimate the responses of these fROIs to various manipulations, we averaged the between-manipulation values across subjects for each manipulation and also averaged the within-manipulation values across subjects for each manipulation. We ran a manipulation (4 factors) by between or within (2 factors) repeated measures ANOVA to test for an overall effect for each region and for any differential effects by the manipulations. Additionally, we ran t-tests to see which conditions had significant effects against 0 in each region.

*Multi-voxel pattern similarity analysis.* To test whether the different types of decisions have distinct neural representation, we investigated whether the patterns of activity between the same manipulation are significantly more similar than the patterns of activity between different manipulations. Correlations between patterns of activity of scan runs served as measures of similarity (Haxby, 2001). We used the anatomical ROIs to extract individual voxel parameter estimates for each scan run's hard > easy contrast. Our design includes two runs of each manipulation allowing us to calculate within-manipulation pattern correlations and between-manipulation correlations. We ran correlations for the 4 within-manipulation pairs and every possible pair of between-manipulations (total of 24 pairwise correlations). We averaged the between-manipulation correlations and the within-manipulation correlations for each subject. We then tested whether both within- and between-manipulations correlations were significantly different from zero across each region, and then ran paired t-tests to test for differences between the two averages for each region.

*Searchlight analysis.* Although our focus was on predefined ROIs, we also performed exploratory whole-brain analysis to determine whether areas outside of our ROIs showed distinct neural representation across our manipulations. For the whole-brain version of MVPA, we implemented a searchlight analysis (Kriegeskorte et al., 2006). Specifically, we defined a small spherical ROI (radius = 3mm) centered on each voxel. In each spherical ROI, we computed the similarities between manipulations and within manipulations, similar to the previous analyses described, which results in each voxel having a similarity measure or correlation for the sphere of voxels surrounding that voxel. To run our searchlight, we adapted script from the CoSMoMVPA Toolbox ([www.cosmomvpa.org](http://www.cosmomvpa.org), Oosterhof and Connolly, 2014). For each subject, we ended up with two brain maps of voxel-by-voxel average correlation coefficients of the within-manipulation comparisons and of the between-manipulation comparisons. We then ran separate group statistics by running a voxel-by-voxel t-test against 0 for each group of maps. We corrected for multiple comparisons by using the false discovery rate (FDR) method (Yekutieli and Benjamini, 1999), as implemented in the FSL software. To look for areas that distinguish the different manipulations, we looked for areas that had greater similarity for the within-manipulation patterns compared to the between-manipulation patterns. For each subject, we created a brain map of the differences between the within-manipulation correlations and the between-manipulation correlations (i.e., within-manipulation minus between-manipulation). We then ran a group statistic over these maps by running a voxel-by-voxel t-test against 0 and corrected for multiple comparisons using FDR.

## **Results**

### **Behavioral Results**

*Manipulation check.* As our fMRI analyses assumed, each of the hard manipulations was rated subjectively more difficult than its respective easy controls. For each of the four manipulations, the hard blocks were rated significantly more difficult than the easy control blocks. ( $ps < .05$ ). See Figure 3a.

Additionally, as expected, for each manipulation except for time pressure, subjects spent significantly more time on hard trials compared to control trials ( $ps < .01$ ). Further, subjects also spent significantly less time during time pressure trials than the control trials ( $p < .01$ ). See Figure 3b. This finding, in conjunction with our results from our subjective ratings, provides evidence that response times were dissociated from the subjective feeling of difficulty. Our subjects viewed our time pressure trials as more difficult, but spent less time on these trials.

### **Group-level fMRI analysis**

The first goal of the fMRI analysis was to identify regions that were activated by the difficult manipulations. Consistent with previous findings, traditional group analyses revealed activity in frontal and parietal areas for the hard > easy contrasts across the four tasks. In particular, we see activation in dorsolateral prefrontal cortex (dlPFC), dorsal anterior cingulate (dACC), dorsomedial prefrontal cortex (dmPFC), supplementary motor areas (SMA), insula and both the inferior and superior parietal cortex. We then overlaid the manipulation specific hard > easy contrasts maps to look for areas of overlap. We found overlap in dmPFC and parietal areas in at least 3 of the manipulations, which could potentially be areas serving as general demand regions. Interestingly, we did not find any overlapping areas for all 4 manipulations. See Figure 4a. Finally, we looked for regions that

only uniquely activated for each manipulation. We found unique activation in middle and inferior frontal gyrus for disfluency, unique activation in visual cortex for multioption, and unique activation in ventrolateral frontal cortex for time pressure. See Figure 4b.

### **Functional ROI results**

Next, we examined whether activation for different tasks overlap at the individual subject level. Figure 5 shows the response profiles of the manipulations across each of regions of the multiple-demand system. We found an overall significant effect for all of the regions ( $ps < .05$ ). We also found an differential effect by condition in three areas, the opercular part of IFG ( $F = 4.62$ ,  $p < .01$ ), insula ( $F = 3.20$ ,  $p < .05$ ), and inferior parietal cortex ( $F = 2.82$ ),  $p < .05$ ). Additionally, we found a differential effect by whether the fROI was defined by the same or different manipulation in the opercular part of IFG ( $F = 16.18$ ,  $p < .01$ ), where the estimates from fROIs defined by a different manipulation showed greater activation.

When we tested the significance of the effect against 0 for each manipulation in each region, we found that most of the regions show reliable hard > easy effects for at least 3 of the 4 tasks. See Table 1. However, across all regions, the results are less reliable for the hard > easy within task effects compared to the between task effects. This could be due to the fact that there are fewer data points for the within-manipulation estimates. The regions that show reliable hard > easy effects include the opercular part of IFG, insula, middle frontal gyrus (MFG), orbital part of middle frontal gyrus (MFGorb), the inferior and superior parietal cortices, precentral gyrus. Interestingly, anterior cingulate cortex show weaker results with



fewer significant hard > easy effects, which is consistent with findings from Fedorenko et al. (2013).

### **Multi-voxel similarity pattern analysis**

Consistent with previous work, our results, thus far, suggest that several common regions in the frontal and parietal cortices are active across different difficult tasks on both the group level and individual level. Our next set of analyses test whether our manipulations have distinct patterns of activation, specifically in the multiple demand system. As shown in Figure 6, we found significant similarities in the patterns of activity across all of our manipulations. For all regions, the between- and within- correlations were significantly different from zero ( $ps < .05$ ; mean within-correlations range from  $r = .20$  to  $.32$ ; mean between-correlations range from  $r = .08$  to  $.22$ ). Interestingly, for all regions but ACC, the within-manipulation correlations were significantly greater than the between-manipulation correlations ( $ps < .05$ ). For ACC, the within-manipulation correlations were marginally greater than the between-manipulation correlations ( $p = .09$ ). This suggests that although there is some similarity in the neural patterns across our manipulations, our manipulations also have distinct patterns of activity throughout the MD system.

### **Searchlight analysis**

Our analyses thus far have focused mainly on *a priori* areas that have been implicated by previous studies. To determine whether any regions outside of our predefined ROIs showed distinct neural patterns across our manipulations, we performed a searchlight analysis, in which we do the same analysis as above for small ROIs centered on each voxel in the brain. Overall, our searchlight analysis corroborates our findings in our previous analyses

(See Figure 7). We found significant similarities in the pattern of activity between different manipulations across the whole brain. Similarly, we also found significant similarities in the pattern of activity between the same manipulations across the whole brain, but these similarities were greater than the similarities between different manipulations. Consistent with our previous MVPA results, we also observed widespread areas that had greater similarity for the within-manipulation patterns compared to the between-manipulation patterns suggesting that these areas can distinguish the patterns of activity for the different manipulations. Most notably, the areas that distinguish the different manipulations include the frontal and parietal regions, which are some of the central components of the MD system.

## **Discussion**

In this investigation, we extended work on cognitive demand and the multiple demand system to investigate whether different forms of cognitive demand have distinct or common neural representation. We used a single decision making task, the delay discounting task, and manipulated this task in four ways to induce different forms of demand. Consistent with previous studies, our group-level analysis and individual-level analysis (fROI) found widespread activation in parietal and frontal cortices, areas considered as part of the “multiple-demand” system (Duncan and Owen, 2000; Fedorenko et al., 2013). Critically, using multi-voxel pattern analysis, we found that even though there are overlapping areas of activation across our manipulations, we also found evidence for distinct neural representation for our different manipulations. This finding was corroborated by our whole brain searchlight analysis investigating similarity among patterns of activity.

Findings from previous studies have suggested a general demand network, the MD system, across the frontal and parietal cortices to be involved with many different forms of demanding tasks (Duncan and Owen, 2000; Duncan, 2010; Fedorenko et al., 2013). We see two possible interpretations of these previous findings on the MD system. The first interpretation is that the MD system may serve as a unitary system serving as a signal for detecting effort or the demands of the task. In other words, the MD system serves as a general index of demand. The other interpretation is that the MD system is a shared network of regions that are commonly recruited across many different tasks, but the way in which the network is engaged depends on the task. Our results support the latter interpretation of the MD system. We found that our different manipulations recruit similar regions in MD system and share some commonality in the patterns of activity. But, we also found that our manipulations have distinct patterns of activity and engage the MD system in different ways.

Our study also builds on previous work in several other ways. First, we used a within-subject design, where each subject saw multiple manipulations within one session. Most studies investigating cognitive demand have only used one manipulation of demand. By using multiple manipulations within a subject, we were able to conduct more fine-grained analyses, like subject-specific fROIs and MVPA. This is critical in investigating whether multiple demands share common neural representations. Second, we collected subjective ratings of difficulty during the experimental session. This allowed us to check whether our manipulations were in fact more demanding to the subject as opposed to assuming our manipulations were more difficult. Third, one of our manipulations, time pressure, dissociated demand from RTs. This is critical because RTs typically increase as tasks become more difficult and are often considered confounds for cognitive demand (Wilcox, 1993;

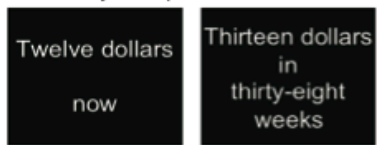
Yeung and Monsell, 2003). It is often difficult to dissociate whether brain regions are encoding the response to demand, or are just simply registering the time on task. In our case, we successfully dissociated time on task from subjective difficulty because subjects rated time pressure trials as more difficult but spent significantly less time on these trials.

Our results also have important implications for furthering our understanding of human decision making. Much work has identified that decisions and preferences are highly sensitive to the circumstances of the decision task, particularly to the demands of the task (see Payne, Johnson, and Bettman, 1993). Yet, less work has focused on identifying the actual decision strategies used and teasing apart why individuals use certain decision strategies. A prominent view of strategy selection involves making tradeoffs between how much effort an individual wants to put forth and the individual's desire to make a good decision (Payne, Bettman, and Johnson, 1993). Although this accuracy-effort tradeoff framework, along with other variations of this framework, has been proposed for decades, very little has been done to test the assumptions of this framework. This is partly due to a lack in process methods that have the sensitivity to pick up the intricacies of a decision strategy. Our study has demonstrated that by using neural pattern analysis, we can potentially start distinguishing decision strategies on a neural level. By combining neural pattern analysis with other sensitive process measures, such as eye-tracking (see Kim, Seligman, and Kable 2012), we can potentially start identifying the neural signatures of different decision strategies to start testing why individuals use certain decision strategies to make a decision.

In summary, our study furthers our understanding of how different forms of cognitive demand are neurally represented. Our different manipulations of difficult decisions

activated regions throughout the MD system. Yet, when we looked at the pattern of neural activity on a voxel level, we found evidence for distinct patterns of activation for our manipulations. Taken together, our study suggests that although different forms of cognitive demand recruit a common set of brain regions, these different demands recruit these regions in different ways.

A Disfluency manipulation



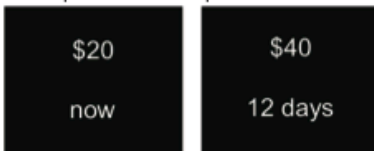
Multiple option manipulation



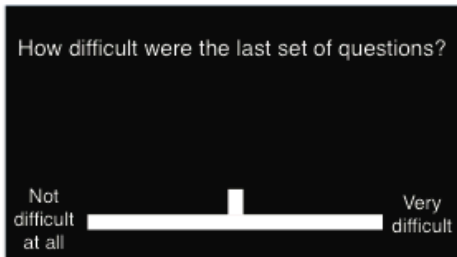
Value difference manipulation



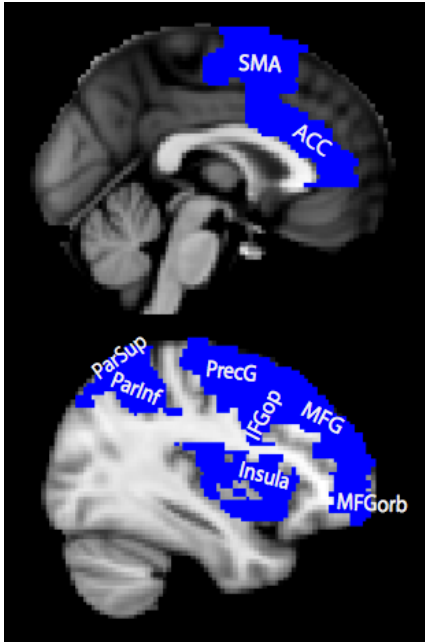
Time pressure manipulation



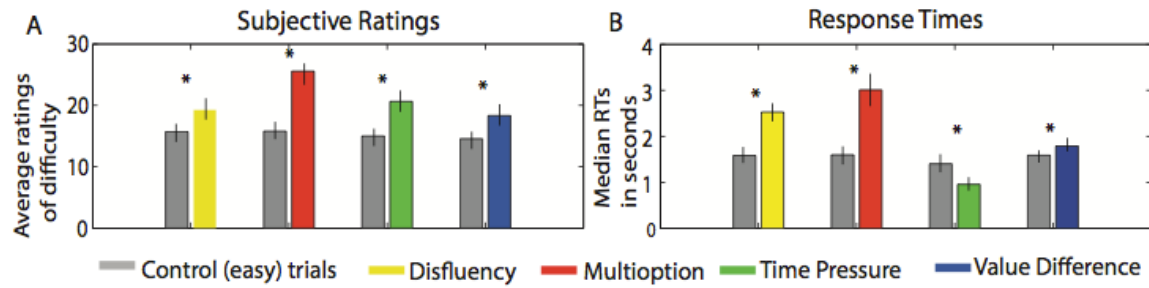
B



**Figure 1.** Illustration of each manipulation and the manipulation check. **(A)** Example of each manipulation type. **(B)** Illustration of what subject saw when prompted to enter their subjective ratings of difficulty.

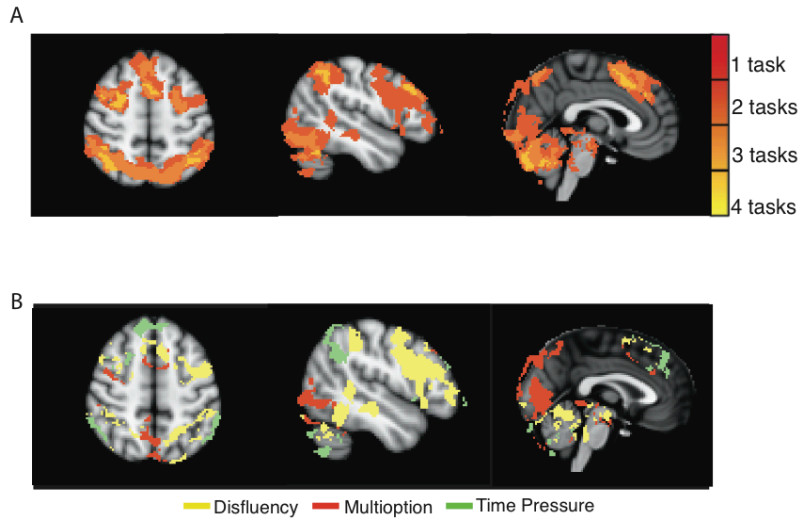


**Figure 2.** Anatomical ROIs of the multiple demand system. ACC, anterior cingulate cortex; IFGop, opercular part of the inferior frontal gyrus; MFG, middle frontal gyrus; MFGorb, orbital part of the middle frontal gyrus; ParInf, the inferior parietal cortex; ParSup, the superior parietal cortex; PrecG, precentral gyrus; SMA, supplementary motor area.

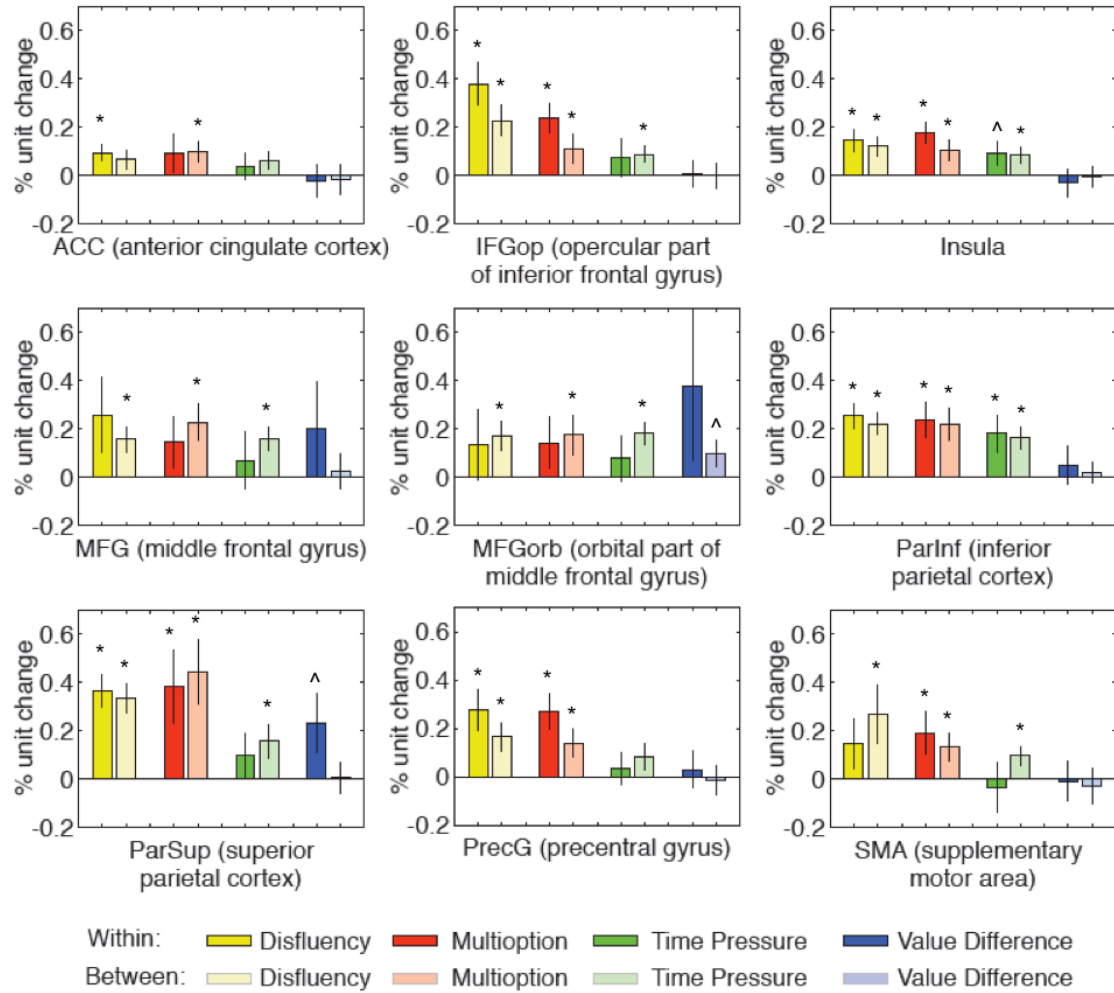


**Figure 3.** Manipulation check and response times. **(A)** Average subjective ratings of difficulty for each manipulation and its corresponding easy controls. **(B)** Median response times for each manipulation and its corresponding easy controls. \*  $p < .05$ ; Error bars represent SEMs.

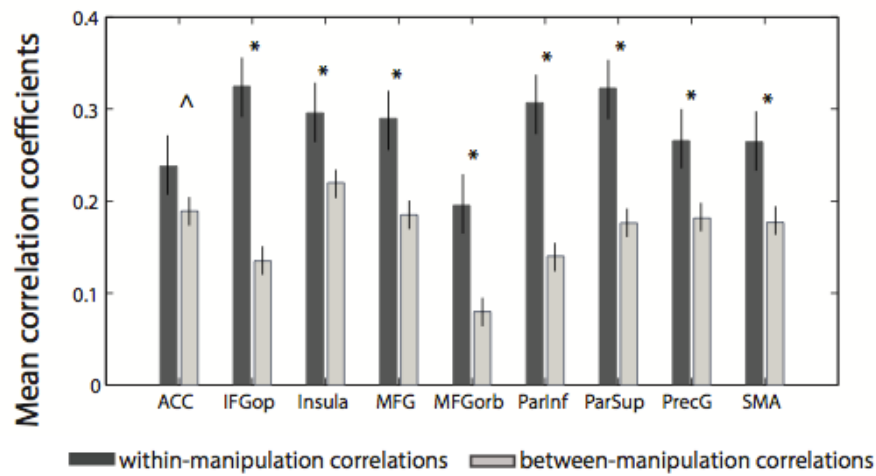




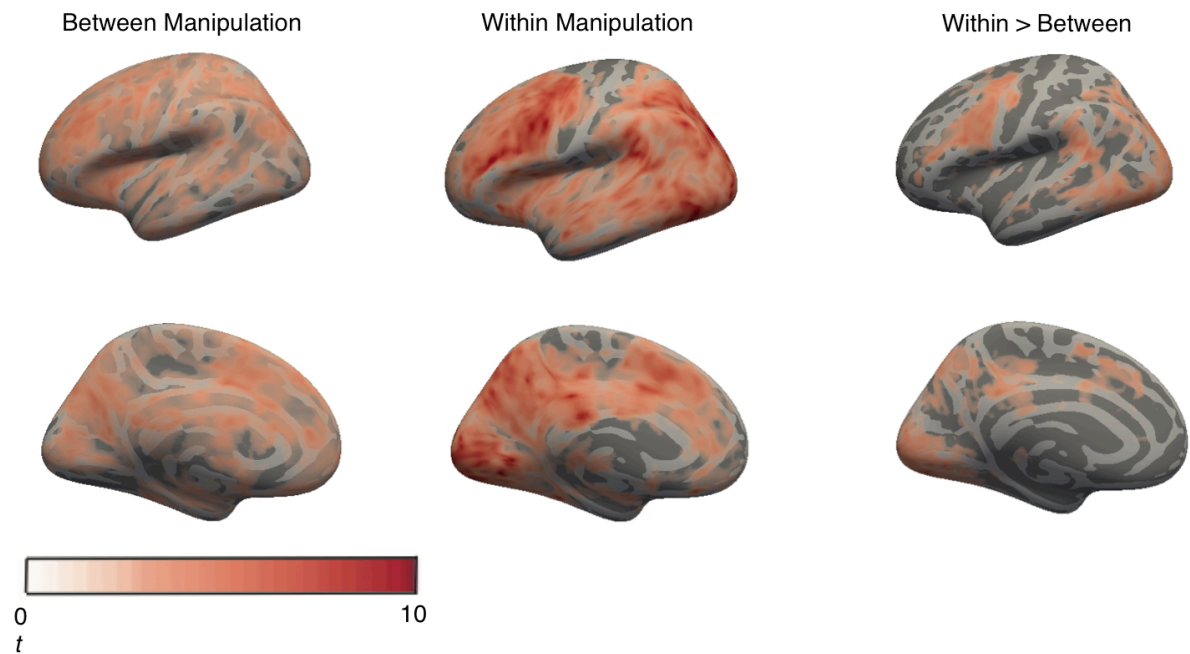
**Figure 4.** BOLD activity for the hard > easy contrasts. **(A)** Neural regions activating for the hard > easy contrast for each of the 4 manipulations ( $z > 2.3$ , cluster corrected at  $p < .05$ ). The activation map shows the overlay of the four hard > easy contrast maps. Brighter colors indicate greater number of tasks overlapping. Three manipulations overlap in dmPFC and parietal cortex. **(B)** Unique activation for each of the manipulations. To find unique activation for disfluency, we first combined the hard > easy contrast maps for the other three manipulations. We then subtracted the combined hard > easy contrast map from the disfluency hard > easy contrast map. We then did this for the other three manipulations. Unique activation for disfluency is in yellow. Unique activation for multioption is in red. Unique activation for time pressure is in green.



**Figure 5.** Average responses across subjects (expressed in percent BOLD signal change relative to baseline) of individually defined fROIs. The darker shades of each represent average responses estimated from an fROI defined by the same manipulation. The lighter shades of each color represent average responses estimated from an fROI defined by a different manipulation. \*  $p < .05$ ; ^  $p < .10$ ; Error bars represent SEMs.



**Figure 6.** Multi-voxel pattern similarity analysis of the multiple demand system. Dark gray bars represent the mean correlations between the same manipulations (within-manipulation correlations). Light gray bars represent that mean correlations between different manipulations (between-manipulation correlations). ACC, anterior cingulate cortex; IFGop, opercular part of the inferior frontal gyrus; MFG, middle frontal gyrus; MFGorb, orbital part of the middle frontal gyrus; ParInf, the inferior parietal cortex; ParSup, the superior parietal cortex; PrecG, precentral gyrus; SMA, supplementary motor area. Error bars represent SEMs. \*  $p < .05$ , ^  $p < .10$



**Figure 7.** Searchlight analysis of similarity measures. First column of results are brain maps of areas showing significant similarities in the pattern of activity between different manipulations. Second column of results are brain maps of areas showing significant similarities in activity between the same manipulation. Third column of results are brain maps of areas that show greater significantly greater similarities for the within manipulation patterns compared to the between manipulation patterns.

	Disfluency		Multioption		Time Pressure		Value Difference	
	within	between	within	between	within	between	within	between
<b>ACC</b>	<b>0.01*</b>	0.13	0.26	<b>0.04*</b>	0.52	0.11	0.76	0.74
<b>IFGop</b>	<b>&lt; 0.01*</b>	<b>&lt; 0.01*</b>	<b>&lt; 0.01*</b>	<b>0.09^</b>	0.36	<b>0.02*</b>	0.94	0.97
<b>Insula</b>	<b>0.01*</b>	<b>0.01*</b>	<b>&lt; 0.01*</b>	<b>0.02*</b>	0.09	<b>0.02*</b>	0.60	0.89
<b>MFG</b>	0.11	<b>0.01*</b>	0.19	<b>0.01*</b>	0.56	<b>0.01*</b>	0.33	0.75
<b>MFGorb</b>	0.38	<b>0.01*</b>	0.20	<b>0.05^</b>	0.44	<b>&lt; 0.01*</b>	0.25	<b>0.09^</b>
<b>ParInf</b>	<b>&lt; 0.01*</b>	<b>&lt; 0.01*</b>	<b>&lt; 0.01*</b>	<b>&lt; 0.01*</b>	<b>0.03*</b>	<b>&lt; 0.01*</b>	0.55	0.69
<b>ParSup</b>	<b>&lt; 0.01*</b>	<b>&lt; 0.01*</b>	<b>0.02*</b>	<b>&lt; 0.01*</b>	0.30	<b>0.04*</b>	<b>0.08^</b>	0.96
<b>PrecG</b>	<b>&lt; 0.01*</b>	<b>0.01*</b>	<b>&lt; 0.01*</b>	<b>0.03*</b>	0.63	0.15	0.69	0.83
<b>SMA</b>	0.20	<b>0.04*</b>	<b>0.04*</b>	<b>0.04*</b>	0.71	<b>0.02*</b>	0.91	0.69

**Table 1.** Results of the t-tests for the hard > easy contrast for each of the 4 manipulations in each of the fROIs from Fig. 5. \*  $p < .05$ , ^  $p < .10$ . Values are bolded for ease of visualization.

## CHAPTER 5 – General discussion

### **Overall Summary**

In this dissertation, I have described research in which we explored the processes that are involved with constructing preferences during decision making. Although the idea of constructed preferences has been around in psychology for decades, this dissertation demonstrated how new techniques, eye-tracking and fMRI, can further elucidate the processes that lead to decisions in different contexts. In chapter 2, we found that preference reversals in response to changes in response mode were also accompanied by changes in visual attention. These results support that the contingent weighting of attributes can at least explain part of the construction processes that lead to preference reversals. In chapter 3, we highlight how eye-tracking can be especially useful in detecting subtle changes in constructing preferences. We found that in response to increasing number of options, all of our subjects reduced the option set to make a decision. Critically, those experiencing time pressure tended to then use a simpler decision strategy to make their decisions, while those without time pressure tended to employ a compensatory strategy. Finally, in chapter 4, we used fMRI data and multivariate pattern analysis to demonstrate that we are able to distinguish on a neural level the different responses to different forms of decision complexity.

The results from this dissertation also opened up many further questions for exploration. Below, I will outline a number of questions and implications that arose from the studies in each of the three chapters.

### **Why people choose certain strategies**

Chapters 2 and 3 demonstrated that eye-tracking data can elucidate the processes involved with constructing preferences and can identify the strategies people use when making a decision. Chapter 4 demonstrated that these decision processes can be distinguished on a neural level using multivariate pattern analysis. A crucial future direction is to then understand why people use certain

construction processes or decision strategies to make a decision. As alluded to in chapters 2 and 3, many different strategies have been proposed, often times for the same decision context. Yet, even as more strategies are uncovered, we still understand very little about why people engage in one strategy over another or why different strategies have been observed in response to similar demands.

Many theoretical frameworks have been proposed for why subjects engage in different decision strategies. Many of these frameworks are based on the idea of “bounded rationality,” the notion that humans have limitations on their capacity for processing information (Simon, 1955). These frameworks are similar in that they involve some sort of tradeoff between the amount of “cognitive effort” to put forth and the desire to make a good or accurate decision. A few examples of these frameworks are the adaptive decision maker (Payne, Bettman, and Johnson, 1993), effort-reduction (Shah and Oppenheimer, 2008), and resource-rationality (Lieder and Griffiths, 2015). A major assumption in most of these frameworks is that decision strategies can be decomposed into units of cost, so an overall effort or information processing cost can be quantified for different decision strategies (Payne, Bettman, and Johnson, 1993). Since eye-tracking can elucidate what information people are processing and the pattern in which they are processing the information and neural patterns of activity can serve as a measure of different strategies, future investigations can use eye-tracking and fMRI to start quantifying the overall costs associated with each decision strategies. However, it is important to note that the other key component of these frameworks is the accuracy of the decision or the desire to make a good decision. In order to fully test the assumptions of these frameworks, future research also needs to figure out a way to quantify “accuracy” or “good decision.”

### **Directionality of the influence between fixations and preferences**

In chapter 2, although we found that preference reversals are accompanied by changes in visual attention, we do not know the directionality of the influence. These differences in fixations might only be an index of the differential weighting of attributes, or alternatively, might also be the

cause of the differential weighting of the attributes. The latter possibility raises some interesting questions for future exploration. If visual attention influenced attribute weighting, then we may be able to reduce or eliminate preference reversals if we forced subjects to look equally at the two attributes. Previous work has found that fixating on an option makes people more likely to choose it (Armell, et al., 2008). Along these lines, we can also manipulate how much subjects fixate on specific attributes to test how these differences in fixation affect overall preference judgments.

### **Effects of construction processes on the neural computation of value**

Recent meta-analytic work has found a common neural currency, a “utility” like neural signal in ventral striatum and ventral medial prefrontal cortex (vmPFC), that tracks the subjective value people place on different rewards during decision making (Bartra, McGuire, and Kable, 2013). An important next step would be to examine how activity in these areas changes in response to changes in the construction processes that lead to a decision. In particular, an interesting question is whether these value-related areas reflect the differential weightings on probabilities and amounts during choices and bids. Thus, in a preference reversal paradigm (chapter 2), neural activity in ventral striatum and vmPFC might be more strongly affected by probabilities during choices and more strongly affected by amounts during bids.

In chapter 3, we demonstrated more complicated processes for constructing preferences. Predictions for how these processes affect neural value computation may not be as straightforward as the predictions for the contingent weighting hypothesis. One prediction would be that BOLD activity in these value regions might just reflect the expected value or utility of the chosen option, which is possible for those subjects who used a compensatory to make a decision. However, in those subjects who rely on just one attribute to make a decision, we might also find BOLD activity to be more strongly affected by the particular attribute than was used to make a decision. Additionally, in chapter 3, our eye-tracking data demonstrated that subjects first evaluated probabilities then moved on a



different strategy before making a choice. An interesting question would be to see if BOLD activity in these value regions tracks these different stages of the decision processes (e.g., track probability in the beginning of the trial, then track expected utility of the option at the end). An fMRI study testing this particular question would involve using both eye-tracking and fMRI at the same time, and would also involve careful timing due to lags in the hemodynamic response.

### **Construction processes of preferences in a natural setting**

In chapters 2 and 3, we measured the processes of constructing preferences in a laboratory environment, which allowed us to isolate and control all variables of interests and make very precise eye movement measurements. However, a laboratory setting may not be representative of the kinds of environments in which people typically make decisions. Future research also needs to examine how well our findings from chapters 2 and 3 generalize to less well-controlled settings. Our analysis techniques can be paired with advances in mobile eye-tracking technology (Boening et al., 2006; Bulling and Gellerson, 2010) to further investigate the construction processes to a wider variety of decision making settings. For instance, future studies could examine decisions that involve many options in grocery stores, restaurants, car dealerships, or other consumer settings. These settings can also provide a more thorough understanding of how visual displays or product placement affects visual attention and preferences, since visual displays in these settings will not be as carefully controlled as it was in a laboratory setting.

### **Distinguishing construction processes not involved with increasing demand on a neural level**

Chapter 4 demonstrated that we are able to distinguish different manipulations of cognitive by investigating the neural patterns. Chapter 3 demonstrated that we are able to identify and measure different decision strategies. However, we focused these investigations only on decision contexts that involved increasing the demands of the task and focused our analyses on a set of neural regions that are known to respond to cognitive demand. An interesting next step would involve testing whether we

can identify different decision strategies, using both eye-tracking and fMRI, from decision tasks that do not involve increasing demand (e.g., framing effects, other changes in response modes, changes in presentation formats). In this type of investigation, searchlight analysis over the whole brain might be a useful strategy in identifying different decision strategies outside of predefined neural regions of interests.

## **Conclusion**

The research described here focused on the cognitive and neural processes of constructed preferences. We introduced new methodological and analytical techniques to further our understanding of how preferences are constructed. A detailed understanding of how people construct preferences is important in understanding how the circumstances of the decision environment affect our overall preferences and choices.

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